

Did Podcasts Help Trump Win Young Men? Gendered Media Spaces and Gender Gaps

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Abstract

In the 2024 election, the gender gap among young voters widened sharply. To examine the role of podcasts in this pattern, we combine two survey datasets with the first large-scale analysis of political content from leading U.S. podcasts, covering 36,659 episodes in 2024. We introduce and demonstrate the occurrence of gendered media spaces, digital entertainment environments where preferences for masculine or feminine content, rather than political ideology, sort audiences and expose men and women to systematically different political messages on non-political podcasts. We examine the extent to which candidate podcast appearances align with gendered interests versus ideology, and whether exposure to conservative content on podcasts is correlated with Trump vote choice among young men. Our results suggest that podcasts are one potentially relevant feature of the media environment surrounding the widening youth gender gap, though they appear to only account for a small portion of the change.

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1 Introduction

Twenty-nine days before the 2024 election, then-candidate Donald Trump appeared on *Flagrant*, one of many entertainment podcasts he would visit during the campaign’s final months. The interview, hosted by comedian Andrew Schulz, opened with questions about fatherhood, family, and celebrity status rather than policy or the election. When the host noted that the interview had spent its time “just” talking about Trump’s family, Trump described the setting as part of “a different world” from the “standard television stuff” that had long structured presidential campaigns. It was, he said, “a whole new, different way of getting the word out,” pointing to the reach these venues offered. The exchange captures a campaign strategy that existing theories of political communication do not fully articulate, as major-party candidates used entertainment-forward podcasts that are not organized primarily around politics as venues for electoral appeals.

We posit that these digital media spaces constitute a novel political communication medium, which we call gendered media spaces, where audiences are often structured around gender identity rather than ideological lean. Donald Trump’s campaign made unusually heavy use of gendered media spaces (specifically podcasts), and many observers credited this strategy with producing the largest shift of young men toward a Republican candidate in modern times (Catalist, 2024; BBC, 2024; PBS, 2024). While the Harris campaign also made appearances on non-political podcasts, Trump’s were more frequent, substantially longer, and concentrated disproportionately in gender-coded venues while Harris’s choices seemed based on ideological lean of podcasts. The Trump strategy also seemingly extended beyond interviews. In August 2024, the Nelk Boys, hosts of the *Full Send Podcast*, launched Send the Vote, a \$20 million voter mobilization initiative aimed at young men, which was debuted in coordination with their podcast interview with vice presidential nominee JD Vance (Leary, 2024; Isenstadt, 2024).¹ This overall entertainment podcast strategy marked a departure from the traditional campaign media strategy of appearing in mainstream news

¹Notably, the *Full Send Podcast* also interviewed Trump as early as 2022.

venues, reflected in Trump’s decision to forgo a *60 Minutes* interview and a second debate with Harris. In this piece, we measure this novel campaign ecosystem on dimensions of gender and ideology to explain its role in the 2024 election, and illustrate the choices Trump and Harris made along these dimensions.

In legacy partisan media, audiences sort on ideology, which means most listeners are already aligned with the candidate’s message and the persuasion value for candidates appearing on these spaces is low (Stroud, 2011; Iyengar and Hahn, 2009; Arceneaux and Johnson, 2013; Levendusky, 2013). In gendered media spaces, audiences sort on identity expression, particularly masculinity or femininity, which is correlated with, but distinct from, political ideology. Post-election commentary picked up on the surface of this pattern, describing Trump’s strategy as a turn toward the “manosphere” or a broader masculine digital media ecosystem (Barrett, 2024; Wolfson, 2024; Haskins, 2024; McCann Ramirez, 2025).² This campaign strategy leverages a listenership that is predisposed toward a candidate’s appeals but has not been filtered through partisan self-selection, creating conditions under which campaign messages can reach citizens not in the audience of standard election outlets.³

The strategic logic of this approach rests on a well-documented cognitive link between gender and political ideology. Americans associate the Republican Party with masculinity and the Democratic Party with femininity at both explicit and implicit levels (Winter, 2010). Individuals’ gendered personality traits predict their party identification, ideology, and vote choice independent of biological sex (McDermott, 2016; McDermott et al., 2021). Endorsement of traditional masculine ideology is associated with conservatism among both men and women, and threats to masculinity increased support for Trump in 2016 (Deckman and Cassese, 2021; Carian and Sobotka, 2018). When a media space signals masculinity through the gender of its hosts, the topics it covers, and the conversational norms it sustains,

²We use the term manosphere here only to describe how popular commentary characterized this strategy. We deliberately avoid using the term ourselves to describe the ecosystem we study; see Section 2.2 for why.

³Clinton’s appearance on *Arsenio Hall* in 1992 is a well-known instance of a candidate using entertainment media, but it was a single high-profile moment rather than a systematic strategy, and is consistent with the soft news literature’s account of generic entertainment-audience reach rather than the gender-coded, directionally predictive venue selection we document here.

it implicitly cues an identity that is psychologically compatible with conservative political appeals even in environments where political content is sparse or absent. Gendered media spaces can therefore function as ideological sorting mechanisms in the absence of overt political content, allowing candidates to locate citizens who do not seek out political media but whose gendered self-expression aligns with conservative appeals.

Younger Americans have long tended to be more progressive than older age groups, but recent work shows growing gender differentiation within this cohort, with young men becoming relatively more conservative and more receptive to traditionally masculine ideas than young women (Deckman, 2024; Tesler, Sides and Marcellin, 2025). Combined with historically smaller gender gaps in this age group prior to the 2024 election, this pattern suggests that young men have become an increasingly receptive audience for Republican appeals. Our theory makes a new claim about how candidates can navigate the podcast ecosystem. In traditional media, candidates generally select outlets that share the campaign’s ideological orientation. In entertainment-focused podcasts, however, gender expression can substitute for ideological alignment when persuasion is the goal. Republican candidates seeking to reach less ideologically sorted audiences should therefore target non-political podcasts with more masculine content, where they may find receptive listeners without relying on an explicitly conservative audience.⁴⁵

Beyond who these audiences are, the medium itself also shapes why podcast venues might be effective for persuasion. The literature on soft news has established that audiences seeking entertainment can encounter political information as a byproduct of that consumption, exposing politically inattentive citizens to content they would not have sought directly (Baum, 2002, 2003). Most podcast listeners enter the medium for entertainment rather than political information, which means political exposure is often incidental (Weeks et al., 2017; Fletcher and Nielsen, 2018; Boczkowski, Mitchelstein and Matassi, 2018; Shearer et al., 2023). This

⁴Our theory predicts a symmetric strategy for persuasion-oriented campaigns, and we return later to why the evidence suggests the Harris campaign pursued mobilization rather than persuasion.

⁵We use entertainment interchangeably with non-political podcasts because non-political provides a clearer genre based differentiation point.

incidental quality makes podcasts especially potent venues for persuasion because listeners with low political interest and weak priors lack the countervailing considerations to resist elite messaging when they encounter it (Zaller, 1992; Prior, 2007). Podcast listeners also report trusting information from podcasts at least as much as from traditional news outlets, and nearly half say their usual listening exposes them to a mix of viewpoints both matching and opposing their priors (Shearer et al., 2023). Since these audiences select into the medium for reasons unrelated to politics, the role of partisan motivated reasoning is reduced, making them more open to messages that would be filtered out in explicitly political venues (Arceneaux and Johnson, 2013).

We test our theory of how elections intersect with the podcast ecosystem with the first transcript-level analysis of the top podcasts in the U.S. with 36,659 transcripts from the 276 most popular podcasts (the top 0.01%) over the 2024 election cycle, January 2024 through January 2025. We describe the podcast ecosystem on two primary dimensions: gender expression (topics and conversational style) and political ideology, both expressed in the transcripts. In doing so we articulate how much political content is in the top podcasts in the U.S., the overall ideological lean of this digital space, and how ideological lean relates to gender expression of the most popular podcasts. We then analyze the choices of which podcasts to appear on made by presidential candidates, and how these appearances correlate with aggregate measures of vote intention of podcast listeners.

Our findings reveal that first, the most popular U.S. podcasts contain substantial political content in both political genre and non-political genre podcasts, and the ideological lean of that content is correlated with the gender expression of the podcast.⁶ Feminine content is positively correlated with liberal podcast lean; and masculine content is positively correlated with conservative podcast lean. Second, we demonstrate that the Trump appearances align more with the gender expression of the podcast than with the ideology of the podcast, in line with our prediction of a Republican strategy to find persuadable masculine voters. Third,

⁶We classify podcasts as political genre or non-political genre using metadata from Edison Research and ListenNotes; see Section 4.1 for details.

relying on consumption data from Edison Podcast Metrics (EPM), we find that exposure to conservative political content in non-political genre podcasts specifically varied by age and gender, with young men receiving the most exposure to conservative content of any cohort.

Fourth, using individual-level listener data from EPM, we show that conservative podcast exposure is associated with higher Trump vote intention after accounting for party identification, with the association concentrated among Independents, and positive associations across all gender-by-age groups. The estimated relationship was similar across age-gender groups, but young men encountered far more conservative content. Counterfactual estimates show that assigning young men the podcast diet of young women significantly lowers their predicted Trump support, while assigning young women the diet of young men modestly raises theirs. However, the size of this association is relatively small, and cannot feasibly explain the entirety of the youth gender gap on its own. We support our EPM analysis with an original panel dataset from YouGov showing self-reported listening to *The Joe Rogan Experience*, the podcast with the most-watched Trump interview of the election cycle, is associated with a higher probability of voting for Trump even after controlling for party identification and prior vote choice. These findings highlight the potential for identity-sorted entertainment ecosystems to create opportunities for even modest persuasion in a highly polarized electorate, where small shifts among otherwise difficult-to-reach voters can matter in closely contested U.S. presidential elections.

2 Motivation

The gender gap in vote choice has long been of interest to political scientists (Norranders, 1999; Center for American Women and Politics, 2024). Since the 1980s, women have supported Democratic candidates at significantly higher rates than men (Box-Steffensmeier, De Boef and Lin, 2004). Much literature has been devoted to investigating the nature of this gender gap, and in particular demonstrating that women do not operate as a monolith. Scholars

have interjected nuance into the gender gap literature over time revealing, for example, that women's support for Democratic candidates has been largely driven by women of color, with white women since 2000 voting largely for Republican candidates (Junn and Masuoka, 2020). We enter the literature investigating a newer area of nuance in the gender gap literature: age. In previous election cycles, the gender gap on vote choice has been strikingly similar across age cohorts. However, 2024 marks a stark increase in difference in the size of the gender gap between age cohorts. We investigate the underpinnings of what scholars such as Deckman (2024) have found, which is that young men are becoming increasingly ideologically conservative and politically distinct from women in Generation Z (Gen Z).

Entertainment media broadly has been shown to be impactful in American Politics (Kim and Patterson Jr, 2025). While much of this literature focuses on television, podcasts also serve as a popular form of entertainment media (Shearer et al., 2023). Research has shown that exposure to television about things such as crime, conspiracy theories, or with progressive portrayals of women meaningfully shift political attitudes about these concepts (Gerbner et al., 1986; Gerbner, 1998; Holbert, Shah and Kwak, 2003; Pfau, Moy and Szabo, 2001). Even more compelling is research that shows that exposure to candidates as celebrities, which develops parasocial relationships, influences people's levels of attachments to them during their presidential bids (Xiong, 2021; Kim and Patterson Jr, 2025). We posit from this literature that podcasts are an influential form of entertainment media that will have political implications similar to television because of these attachments and the influence of entertainment related political content on attitudes.

Podcasts are episodic audio (and sometimes visual) programs made available for listening on a wide variety of platforms (e.g., Spotify, Apple Podcasts, and YouTube) through Really Simple Syndication (RSS) feeds. They are largely entertainment based in nature, and according to Edison Research 55% of Americans are monthly podcast listeners (Edison Research, 2025). Podcasts are also particularly popular with younger generations, with 66% of 12-34 year olds saying they have listened to a podcast within the last month (the largest

percentage of all age cohorts) (Edison Research, 2025).⁷ Young people mostly get their podcasts on YouTube, and not just Spotify or Apple Podcasts (Edison, 2024). According to Edison Research, 84% of Gen Z podcast listeners get their content with a video component such as YouTube (Edison Research, 2023). This means the reach of podcasts goes beyond their popularity on traditional audio only platforms. Overall, podcasts are a widely consumed medium that reaches across demographics, with especially high penetration among younger cohorts, making them a potentially significant site of political information exposure for the electorate broadly.

2.1 Parasocial Media Effects and Persuasion

Podcasts represent a compelling new medium for persuasive content because they can approximate some of the social connection that is critical for persuasion. As elaborated by Lazarsfeld, Berelson and Gaudet (1968), mass media does not have much of a persuasive effect on its own. Rather, interpersonal communication – and trickle-down opinions through communal thought leaders – drives persuasion. Podcasts can therefore replicate, to a limited extent, the social aspects that are necessary for persuasion to occur. Research into the behavior of podcast listeners suggests that they develop “parasocial” relationships with podcast hosts, meaning that they act as if they have a social connection with the host, despite never meeting them in person (Schlütz and Hedder, 2022; Soto-Vásquez, Vilceanu and Johnson, 2022; Tobin and Guadagno, 2022).⁸ These parasocial bonds with hosts are heightened by the perceived “authenticity” of the podcasts, which increases through a combination of competency and unpredictability (Schlütz and Hedder, 2022). Maloney Yorganci and McMurtry (2024) finds that ordinariness, immediacy, and similarity are some of the most important qualities of podcast hosts that help facilitate these bonds.

⁷Edison podcast metrics include 12-18 year-olds. Thus when we refer to reports of Edison Research such as the above, it includes 12-18 year olds. However, in our analyses later in this paper using Edison data we omit those not in the voting age population.

⁸Parasocial interaction refers to the “illusion of face-to-face relationship with the performer,” where audiences experience media personae as if they were engaged in real social interaction (Horton and Richard Wohl, 1956).

Online podcast communities are built through intimacy, or the perception of intimacy (Sienkiewicz and Jaramillo, 2019; Rodgers, 2023). In an analysis of political podcasts published by NPR, Euritt (2019) observes that the podcast format facilitates a stronger feeling of participation in discourse, and that producers intentionally shape the presentation in ways which allow the audience to feel present and involved. While podcasts are not as participatory as social media, they excel in this domain relative to traditional radio shows (García-Marín, 2020; Andok, 2025). High level research shows that much of the engagement with podcasts is driven by this emotional attachment to the podcast community and host (Chan-Olmsted and Wang, 2022). This attachment is facilitated by the long-form, conversational nature of podcasts, which listeners typically consume repeatedly and during solitary activities like commuting or exercising, producing deep familiarity with hosts' voices, opinions, and personalities over time. The community forms around shared identification with the host's perspective and accumulating in-group references across episodes. By facilitating perceived closeness with podcast hosts, podcasts may have a persuasive power beyond what has traditionally been seen with mass media.

The persuasive power of these parasocial bonds is amplified by the medium itself. Audio and visual cues in advertising are more compelling than text or pictures alone (Chaiken and Eagly, 1976; Appiah, 2006; Wittenberg et al., 2021), particularly when delivered by a host the audience already trusts, and that trust translates directly into purchasing behavior. Over 30% of podcast listeners trust their podcasts more than traditional media (a plurality trust it just as much), and host endorsement drives real consumer action, with 46% of weekly listeners reporting they have purchased something based on a host recommendation or advertisement, and a third of active listeners saying they made a lifestyle change after podcast consumption (Shearer et al., 2023). Podcast consumption is also linked to measurable positive changes in health-related behaviors (Robins et al., 2024). Together, this evidence shows that podcast hosts develop a form of credibility with their audience that translates into behavioral compliance; listeners act on what a trusted host recommends, purchasing products

or adopting habits, even in domains outside the host’s actual expertise.

This is distinct from direct campaign contact, which meta-analyses of field experiments find has near-zero persuasion effects in general elections (Kalla and Broockman, 2018). Podcasts operate through different mechanisms. Repeated long-form consumption builds trust that a single canvassing visit cannot replicate, and incidental exposure reaches listeners who are not processing content through a partisan lens. As a result, these listeners lack the motivated reasoning that would otherwise filter out cross-cutting appeals (Arceneaux and Johnson, 2013).

Lastly, we look to the literature on talk radio in American elections to understand the persuasive potential of podcasts as many consider podcasts to be the new evolution of talk radio. We use them as another media environment which is predominantly audio based, has a host audiences can get attached to, and falls into the new digital media environment rather than traditional media. Podcasts may be even more potent than talk radio because they extend the host-audience relationship into persistent online communities through comment sections, subreddits, Discord servers, and YouTube comment threads. These reinforce bonds in ways that traditional radio listeners, often isolated in their cars with no other connection to the community, would not have fostered.

Talk radio research offers the clearest evidence that persuasion can occur even within audiences that skew ideologically. Barker (1999) and Barker (2002) show that consumption of conservative talk radio hosted by Rush Limbaugh was meaningfully associated with increased support for Republican candidates across elections, net of predisposed conservative attitudes. We use this literature to help inform the selection issue also faced in the podcast ecosystem. Since listening habits correlate with underlying political attitudes, estimates of media exposure effects must control for predisposed partisanship and ideology.⁹ Two further findings on selection issues from this literature bear directly on podcasts and we use to inform our approach.

⁹We return to this identification challenge in the following section.

First, Barker (1999) shows that Limbaugh’s audience was not uniformly conservative in either policy views or ideological strength, meaning persuasion remained possible even within this ostensibly sorted environment. A similar pattern holds for contemporary podcast audiences. Work on alternative and heterodox digital media shows that listeners of ostensibly right-leaning shows often self-identify as “free thinkers” or independents rather than conservatives, and engage with political content in ways not reducible to ideological commitment (Munger and Phillips, 2022; Lewis, 2018; Heft et al., 2021). Second, talk radio listening is driven mostly by a desire for entertainment (Herbst, 1995), so audiences select into shows to maximize gratification rather than to avoid cognitive dissonance (Barker, 2002). We show a similar pattern for podcasts. Ideological self-sorting is evident among political genre podcasts, but far less so among non-political genre podcasts, exactly the entertainment-driven, less-sorted audience talk radio research suggests should be persuadable. Talk radio exposure has also been linked to lower system efficacy and higher conventional political participation (Barker and Knight, 2000; Hollander, 1996), underscoring that these media environments shape political attitudes and behavior beyond vote choice alone. Yet despite this rich literature on talk radio, no research to date has assessed whether this same persuasive potential extends to the modern podcast environment.

2.2 Gender, Podcasting, and Political Psychology

These parasocial mechanisms explain how podcasts might persuade, but not who is most likely to be reached by that persuasion. We argue that gendered cues in non-political podcast spaces function as an ideological sorting mechanism distinct from the partisan selective exposure documented in traditional media environments (Stroud, 2011; Iyengar and Hahn, 2009). While selective exposure theory assumes audiences sort themselves on ideology, we show that audiences can sort on gender expression in ways that produce ideologically congruent listenership without a high degree of overtly political content being present. We call this gendered ideological sorting, and it is the core mechanism through which candidates

reach persuadable voters in gendered media spaces via ostensibly non-political podcasts.

The podcast environment is deeply gendered. Listeners exhibit homophily, gravitating toward hosts who share their own gendered self-presentation, while the masculine and feminine cues embedded in a podcast's content and presentation are key factors by which politicians can make use of entertainment-forward spaces. Both mechanisms operate through expressive practices, how someone talks, what they talk about, how they present themselves, rather than only through the fixed demographic identity of who is speaking. For this paper we operationalize gender similar to how West and Zimmerman (1987) conceptualize it. Gender is not just a label, but something people “do” through the repeated practices of everyday life, the day-to-day actions and expressions that can be classified along a spectrum from masculine to feminine. Examples of these things include the pronouns people use, their hobbies, how they choose to wear their hair and dress, the roles they take on in their families and at work, and even how they speak. We classify these actions and expressions along a spectrum whose masculine and feminine poles represent socially recognizable clusters of practices, styles, and expectations associated with men and women, rather than traits that all men or all women naturally share.¹⁰

For this project, we isolate components of gendered expression that can be measured in podcast transcripts and distinguished from ideology, our other primary concept of interest. We focus on two analytically distinct dimensions, topics and speech styles. Examples of this include sports and finance which are coded as masculine versus beauty and relationship advice which is coded as feminine. In terms of linguistic and behavioral styles of speech we use cues such as directive, competitive language which are coded as masculine, and hedging, consensus oriented language, or emotional disclosure coded as feminine. These concepts

¹⁰We acknowledge that a strict masculine-to-feminine spectrum is in tension with gender performativity frameworks which challenge the gender binary. Specifically, they would oppose the idea of masculinity and femininity as stable endpoints of a spectrum and that all gender expressions could be placed between them (Butler, 1990, 1993). However, we adopt the spectrum for measurement purposes because we are looking to capture societally accepted, or in other words stereotypical gendered expression, in transcript content as we think this is what will largely be expressed and observable in the podcast ecosystem. The spectrum is a pragmatic measurement choice and a first step towards articulating the space, not a theoretical claim that gender reduces to a binary.

allow us to capture how gender is performed and communicated in everyday contexts (like podcast conversations) in ways that are politically relevant but not reducible to ideology. We use the terms gendered cues, gender(ed) expression and gendered lean interchangeably to reference how masculine or feminine these podcasts are. When we employ gender from a measurement perspective, we use a scale from masculine to feminine to describe both the topics that are discussed and the conversation style of each speaker. We do this at the granularity of each individual utterance throughout the conversation that takes place over an entire episode. This allows us to measure how gender expression shifts over the duration of episodes and aggregate individual speaker scores to the episode and podcast level. We further combine this data with the self-identified gender of the host, weighted at 10% against the 90% transcript-derived score, which appears in our data as man, woman, or mixed gender group.¹¹

Measuring gendered expression on a spectrum rather than reducing it to host identity is more nuanced and theoretically appropriate for our argument. Men and women can convey masculine and feminine cues in cross-cutting ways where a woman host can lead a highly masculine conversation, and a man host can engage in feminine-coded speech and topics. Collapsing gender into the self-identified categories of man or woman would miss these cross-cutting performances, which are the kind of cultural signals that structure audience sorting and ideological cueing.

To understand why politicians would choose gendered podcasts to find new voters or latent ideologues we look to the political psychology literature. In our focus on particularly the digital sphere young men inhabit, we avoid the term manosphere to describe the broader digital masculine ecosystem we are analyzing since scholarly literature denotes the

¹¹The blend assigns male hosts +1, female hosts -1, and mixed or unknown hosts 0. The small host-identity weight serves as a structural anchor. A podcast hosted by a man carries a masculine signal even in weeks when the transcript content happens to be gender-neutral due to topic selection or guest influence; without any anchoring, transcription artifacts or atypically gender-neutral episodes can produce misleading reversals in a podcast's overall score. Weighting host identity at only 10% ensures that transcript content dominates while preventing those reversals. Results are robust to alternative specifications including the pure-transcript score with no host-identity weight.

manosphere as a specific online ecosystem organized around explicit anti-feminist ideology and gender grievance (Ging, 2019; Ribeiro et al., 2021). Post-election coverage extended the label to a much broader set of mainstream masculine entertainers which obscured the boundary between explicitly anti-feminist communities and mainstream masculine entertainment (Barrett, 2024; Wolfson, 2024; Haskins, 2024; McCann Ramirez, 2025). The mainstream masculine entertainment spaces we study are structurally distinct, with misogyny as an occasional feature rather than its being a key component of the podcast’s ideology. *Gendered media spaces* keeps the analytic focus on the structural feature we care about, masculinity.¹²

Prior research shows that masculinity is correlated with ideological conservatism in the minds of voters (Winter, 2010; Deckman and Cassese, 2021; Karpowitz et al., 2024). Many attribute this link between masculinity and conservatism to issue polarization over issues such as the Equal Rights Amendment and abortion, more women running for office and winning as Democrats, and the continued attention to the gender gap in vote choice since 1980 (Adams, 1997; Wolbrecht, 2010; Elder, 2008). Political psychology offers three complementary accounts of why this link exists, operating through implicit association, direct trait-level prediction, and masculinity threat, respectively.

The first operates through implicit cognitive association. Winter (2010) finds that perceptions of the two major political parties in the United States are cognitively intertwined with perceptions of gender. The Democratic Party is implicitly associated with femininity and the Republican Party with masculinity at the level of automatic cognition, operating below the threshold of conscious partisan identification. This means masculine cues in a media environment can activate Republican-aligned schemas without listeners ever processing the content as political. Thus, when candidates appear on heavily masculine podcasts such as Joe Rogan, they are able to connect with men who may not ordinarily engage with explicitly partisan right wing media, yet who resonate with masculine framing which is already cognitively linked to Republican partisanship. This allows candidates to reach audiences

¹²When we use the manosphere in this research we are referencing the scholarly identified manosphere rather than popular accounts.

outside the conservative base by drawing on gendered associations that are psychologically compatible with Republican ideas. In other words, these appearances expand reach beyond the traditional conservative base because they are finding people not already ideologically self sorted in the conservative media ecosystem, but those who might be predisposed to appreciate conservative ideals that comport with the masculine ecosystems they are in (see Appendix Section B).

The second operates through direct trait-level prediction rather than implicit association. Individuals' gendered personality traits predict their party identification, ideology, and vote choice (McDermott, 2016; McDermott et al., 2021). Where the association pathway works through cognitive schemas activated by external cues, this pathway works because a listener's own gendered self-concept guides their political leanings, giving masculine-coded podcasts a second, independent reason to draw conservative-leaning audiences beyond whatever cues they cognitively activate.

The third operates through masculinity threat rather than association or trait prediction. Carian and Sobotka (2018) finds that psychological threats to masculine identity increased individual-level support for Trump in 2016, with men responding to that threat by favoring a candidate who signals restored masculine status. If the more extreme masculine-coded podcasts traffic in narratives of men being under attack, whether from feminism, changing gender norms, or economic precarity, exposure to this content offers a third, independent route to conservative persuasion beyond the associative and trait-based pathways above.

Beyond these three individual-level psychological pathways, gendered cues in podcasting (how masculine or feminine a podcast is) also structure how audiences are curated, sorted, and discovered through parasocial identification, where listeners gravitate toward hosts who reflect or embody their own gendered self-concept. This produces audience sorting patterns analogous to gender homophily documented on other social media platforms (Thelwall and Foster, 2021; Pignolet, Schmid and Seelisch, 2024), where men most often engage with male creators and women with female creators. We demonstrate this sorting pattern empirically

in our analysis of the third hypothesis relating audience gender composition to podcast-level masculinity scores.

Taken together, these dynamics suggest that masculine podcast spaces serve as effective infrastructure for conservative appeals (feminine spaces equally for liberal appeals). Parasocial bonds give hosts persuasive leverage over their listeners. Gender homophily and gendered identification sort audiences along lines that are cognitively linked to partisanship without requiring ideological selection. And the cultural content of masculine-coded podcasts resonates with the gendered politics that animate contemporary Republican appeals. The combination of these mechanisms may help explain why Republican candidates, and Trump specifically, sought out masculine podcasts in 2024. These were spaces where the audience was already sorted in ways favorable to conservative messaging, and where parasocial trust in hosts could translate into openness to candidate appearances.

3 Theorizing Gendered Media Spaces

We theorize that podcasts were influential in the 2024 election because of incidental exposure to political messaging. The majority of podcast consumers seek entertainment, not political content. Nevertheless, many prominent entertainment podcasts do discuss political issues and elections. Thus, individuals who consume podcasts will likely be exposed to some amount of political content. We propose that this exposure will be systematic, based on the individual's affinity for certain styles of podcasts — specifically with respect to gender. Because there is a correlation between gendered interests and ideology, individuals who tune in to more masculine podcasts will be more likely to hear conservative content. Similarly, individuals who listen to more feminine podcasts will be more likely to hear liberal content. In the context of an election, this presents an opportunity for candidates to reach segments of the population who may not initially be politically active, but whose underlying interests are amenable to a specific ideological view. This has implications for candidate decision-

making, what we should expect about voting behavior among podcast consumers, and the potential for podcasts to persuade potential voters.

Our theoretical argument rests on three linked claims introduced above. First, at the individual level, gendered interests and dispositions are cognitively linked to political ideology, with masculinity associated with conservatism and femininity with liberalism (Winter, 2010; Deckman and Cassese, 2021). We treat this established psychological relationship as a background premise rather than an empirical claim tested in this paper. Our hypotheses instead examine how this relationship is reflected in podcast content, candidate strategy, audience sorting, and downstream political behavior. Second, this individual-level link is reflected in podcast content, where gender expression and ideological content covary. This covariance emerges through multiple pathways: hosts whose own gendered dispositions shape their content, audience demand that rewards gendered-ideological coherence, and candidate and elite actors who strategically target gender-coded podcasts to inject ideologically congruent content into those spaces. Third, audiences sort into non-political podcasts based on interest in the gendered nature of the podcast (as opposed to the political slant). Taken together, this means listeners of masculine-coded podcasts are exposed to conservative content even when they are not seeking political information. These theoretical mechanisms then potentially produce changes in voting behavior. Our hypotheses test the observable implications of the latter two claims and their potential downstream consequences. H1 tests the content-level correlation, H2 tests candidate responses to the resulting ecosystem, H3 tests audience-content matching, and H4 tests the relationship with voting behavior.

3.1 Candidate Strategy

Given constraints on time and budget, a candidate for office must optimize their use of resources. To do so, they will devote money and energy towards reaching individuals for which campaign contact can have an impact. This means either turning out the existing base or finding new persuadable voters. Within the podcast space, we argue that individuals who

tune in to overtly political podcasts are already likely to vote, and to vote in concordance with the ideological lean of their preferred podcast. They are not persuadable by the opposing side and only an efficient target for mobilization of the existing base. The strategically valuable audience lies with individuals tuned in for topics other than politics, who are less ideologically entrenched and therefore potentially movable.

Because of this, we focus on podcasts that don't advertise or consider themselves as primarily political for our key analyses. While we present holistic accounts of the top podcast environment as it is a new digital medium for political engagement and it is important to map, our analyses of candidates and votes are focused on non-political genre podcasts. As our data demonstrate, many of these podcasts do discuss political topics in line with theories of incidental exposure to politics (occasional politics coming up in non-political spaces). As noted previously, the value in these entertainment-forward spaces is listeners encounter political content in a less defended posture because they did not tune in for politics, and that content arrives through a trusted host rather than a partisan source. Additionally, hosts cultivate intimate, parasocial relationships with their audiences, and a candidate who fits the host's style can inherit some of that trust by association.

Candidates must therefore identify which online spaces are inhabited by people who can be convinced to vote for them, and a candidate should identify topical interests compatible with their campaign messaging and partisan identity. Podcast audiences sort themselves not just by topic but by identity-coded clusters of topics, and these clusters track gendered patterns of consumption that correlate with partisan lean. We propose that two gender-coded features of podcasts, speech patterns and topical interests, are highly compatible with ideology in the podcast ecosystem.

H1: In podcasts, masculine (feminine) topical interests and speech patterns will be positively correlated with ideologically conservative (liberal) political content.

Consequently, we predict that when candidates appear on non-political podcasts, they

will select venues based on gender expression rather than ideology.¹³ Because gender and ideology are correlated in podcast content (as stated in H1), any candidate-appearance pattern could be explained by either dimension. Our claim is that gender expression adds explanatory power beyond ideology where candidates target masculine-coded podcasts not only because those podcasts are conservative, but also because masculine coding signals an audience compatible with Republican appeals, and feminine coding an audience compatible with Democratic appeals.

H2: Gender expression of podcasts will predict candidate appearances on non-political podcasts.

Our theory predicts that both Democrats and Republicans could utilize gender expression (either feminine or masculine) targeting to find unsorted but ideologically compatible audiences for persuasion. However, this theory of gender expression targeting is specific to persuasion rather than mobilization (i.e. finding less partisan predisposed voters rather than rallying the base). If a campaign is trying to mobilize a base that is already inclined to their messaging then targeting on a correlated but separate dimension from ideology like gender expression in non-political spaces to find audiences offers no particular advantage. Whether a given campaign in 2024 appeared to pursue a persuasion-oriented gendered strategy or a mobilization-oriented one is therefore an empirical question we return to in the results section.

3.2 Audience Behavior

We treat gender expression and ideological content as playing distinct roles in the podcast environment. Gender expression structures audience sorting and candidate venue selection, while ideological content captures the political message to which those audiences are exposed.

¹³We provide additional support for the gender versus ideology pattern of selection in Section B which shows that the majority of the audience in Trump appearances were not Republicans. The analyses which test H2 should be interpreted with context provided by Figure A1 which shows that the audience isn't already ideologically entrenched or predisposed.

On this account, masculine-coded podcasts are important not because masculinity itself directly implicates Republican voting, but because these podcasts both attract the audiences most relevant to Republican outreach and serve as conduits for conservative political content.

This framework implies that gender expression should systematically structure audience composition.

H3: Podcasts with more masculine gender expression will have audiences that are disproportionately men, and podcasts with more feminine gender expression will have audiences that are disproportionately women.

We expect that podcast listeners who are actively engaged in politics probably do not need additional encouragement to turn out to vote, and are not likely persuadable. We are more interested in understanding the habits of individuals who may be incidentally exposed to political messaging. We propose that because gendered characteristics have a high correlation with ideology, podcasts which have a clear gendered lean are likely to attract not only individuals of that gender identity, but also individuals who have policy preferences compatible with either a conservative ideology (Republican) for masculine content, or a liberal ideology (Democrat) for feminine content.¹⁴

If the above hypotheses hold, then podcasts represent a space where candidates can systematically reach populations which are amenable to their policy platforms and who can be persuaded to vote. However, it is challenging to actually measure and isolate the impact of any campaign messaging strategy, especially post hoc and without experimentation. As a first step toward understanding the impact of podcast content, we evaluate if certain segments of the population were exposed to high levels of conservative content in non-political spaces. We then connect conservative exposure to vote intention and vote choice at the individual level, controlling for partisanship in both datasets and prior vote history where available, to show whether incidental exposure through podcasts correlates with shifts in 2024 voting

¹⁴We link ideology and party ID because the Edison data only asks for party ID. Our content data focuses on ideology, but the consumption data we were able to obtain only features party ID.

behavior.

Why should we expect conservative content exposure to correlate with voting behavior even among listeners who are not seeking political information? The persuasion mechanism for incidental podcast exposure differs from the mechanism operating in overtly partisan media. Listeners of entertainment podcasts are not selecting content to affirm political identities and therefore do not engage in the motivated reasoning that structures partisan media consumption (Arceneaux and Johnson, 2013). We expect entertainment forward podcast listeners to hold weaker political priors because they are less engaged than those who seek out predominantly political content, and Zaller (1992) argues that individuals with weak priors lack the countervailing considerations needed to resist elite messaging when they do encounter it. This combination (reduced motivated reasoning, weak priors, and parasocial trust in hosts) creates conditions in which incidental political exposure can meaningfully shape attitudes. The claim is not that entertainment podcasts produce dramatic vote switches, but that exposure to conservative content in masculine-coded spaces can activate latent conservative dispositions in listeners who are not already sorted into partisan media ecosystems.

H4: Individuals exposed to higher amounts of conservative content through non-political podcasts in 2024 will be associated with higher Trump vote intention and vote choice, conditional on their own party identification and, where observed, prior vote history.

4 Data and Methods

In this section, we describe how we constructed our dataset and outline key parameters related to its scale. We explain how podcasts were selected, how transcripts were generated, and how large language model (LLM) based labeling was conducted.

4.1 Selecting Podcasts

There is a variety of content which could be considered a “podcast.” For our purposes, we define podcasts as pre-recorded audio content that is distributed online via an RSS feed, consistent with prior large-scale podcast corpus collection methodology (Litterer, Jurgens and Card, 2024). For a podcast to distribute through Spotify and iTunes, an RSS feed is generally required. Importantly, RSS feeds are publicly available and used for distributing a wide variety of content beyond podcasts, such as blogs or news articles. Relatedly, not all podcasts distributed via RSS feeds are what one would traditionally consider a podcast; for example, after COVID, many religious congregations began broadcasting weekly services online, and some created and continue to maintain RSS feeds of these services, which are included in our definition of podcasts. There are also a handful of content creators who market themselves as “podcasters,” but who publish exclusively to YouTube or another video-first platform which does not require an RSS feed. We only include those who have an RSS feed since it is a requirement for downloading the MP3s in a sustainable way, and do not include any creators who claim to be podcasters but post only on other venues such as YouTube.

We used ListenNotes as the main provider to get a seed list that compiles RSS feeds for podcasts.¹⁵ This seed list (a static list as of December 2024) amounted to over three million podcasts globally. In this paper, we focus on the top U.S. podcasts. While this limits us to some degree as there are many podcasts that do not meet our popularity threshold that will be omitted, this choice was made to maximize number of listeners alongside transcription limitations. When we generalize about the podcast ecosystem from here out, we are specifically looking at the most popular podcasts, and we cannot guarantee the findings hold to the whole space (smaller audience podcasts), but the findings hold true for the podcasts which reach the most people. To select on popularity, we started with the popularity score generated by ListenNotes. They generate this score by analyzing both data traffic on their

¹⁵listennotes.com

website, and popularity and engagement metrics across several other domains. Using this metric, we selected the top 0.01% of podcasts.¹⁶ We then verified the popularity scores from ListenNotes with rankings from Edison Research, who use survey measures to make a holistic list of the most popular podcasts. Podcasts that ListenNotes ranked highly but that Edison’s survey data did not corroborate were replaced with podcasts for which both sources agreed on popularity. This resulted in a final set of 276 podcasts, which represent the most popular podcasts in the U.S. in 2024.

We then scraped all available episodes from 2024 for these 276 most popular podcasts, resulting in a dataset of 36,659 episodes. For each episode, we downloaded the MP3 from the RSS feed and transcribed and diarized the recording using WhisperX (Bain et al., 2023). WhisperX uses OpenAI’s open-source transcription software, Whisper, but adds diarization which splits chunks of text by speaker, to the output. This means that the transcription notes when audio is coming from different speakers, and can track conversations rather than outputting one continuous stream of text.¹⁷ We use each speaker utterance as the unit of analysis for the LLM, and use the term speaker chunk, or chunk, throughout the paper to refer to each labeled speaker output from WhisperX. We recognize a limitation of this approach is that we do not distinguish host from guest utterances, or differentiate among multiple hosts. Rigorously modeling these speaker-role differences lies beyond the scope of this paper, so we instead treat each episode as an aggregate signal and focus on its holistic message.

We annotate each podcast’s genre as political or not using metadata provided by Edison Research, which they source from the podcast’s self-identified genre tags on Apple Podcasts (determined by the podcast). We validate this metadata using a more detailed set of podcast genre tags from ListenNotes which uses proprietary tags in addition to the parent tags on

¹⁶We removed any podcasts that were focused on children’s content as we are primarily focused on the voting age population.

¹⁷Details on the specific settings, including the size of the model, batch configuration, and validation procedures are included in Appendix K.

Apple to ensure podcasts are accurately labeled as political or not.¹⁸ We then use these genre tags to separate the data into incidental versus overt political exposure at the podcast level (political vs. non-political podcasts).

We use genre, rather than our own classifier’s estimated political content, as the deciding factor separating political from non-political podcasts. Genre reflects how a podcast advertises itself and attracts new listeners, a signal set by the podcast’s own publisher and independent of anything we measure from the transcript. Defining the boundary from our own political-content scores instead would risk building our central finding into the data by construction. While we will show later that many non-political shows discuss politics often, and that this boundary can therefore be contested, we show in the results that genre remains an informative dividing factor in patterns across the ecosystem.

4.2 LLM Labeling

We use an LLM to label the gender and ideological expression of transcript segments given the scale of the data (~ 8.5 million speaker segments) and use humans to validate the performance of the model. WhisperX transcribes audio recordings and segments the transcript based on when the speaker changes. We conduct our data labeling and analysis on these speaker chunks that can be as short as a single word or phrase, as is common in conversation, but are often roughly paragraph length, which is typical of the type of dialogue taking place in podcasts and talk shows. We pass the transcript text for each speaker chunk to Gemini 3 Flash Preview and label it for expressed gender and ideology.¹⁹

For each podcast, we score every individual episode using the transcript chunk as the unit of analysis. The classifier operates in two separate stages for each content dimension

¹⁸ListenNotes’ 160 genre tags roll up to 21 top-level parent categories via a parent ID field. Beyond News (ListenNotes parent genre which maps to Apple’s own News category that EPM uses), the additional ListenNotes subcategories we treat as political are: Politics, News Commentary, Daily News, and Government.

¹⁹LLM annotation was conducted using the batch API in Portkey with models hosted in Vertex AI. To account for Gemini 3 Flash Preview’s context length as well as substantive performance on large text inputs, we limit each speaker chunk to a maximum of 750 characters and split it into sub-segments if it exceeds that max. All speaker chunks are split in such a way that no text is missed and the entirety of an episode is scored.

and the classifier evaluates gender and ideology independently so that the ideology label is not influenced by the gender label and vice versa. The first stage is detection, where the model determines whether a given speaker chunk separately contains either gender-expressive or political content.²⁰ In this stage, we define gender-expressive content separately as gendered behaviors (how masculine or feminine the style of speech is, see Appendix Section I) and gendered topics (how masculine or feminine the topic of the segment is, see Appendix Section I). All speaker chunks that get positively identified in the first stage go to the second stage for scoring, while chunks that are not flagged in the detection stage are assigned a score of zero for that dimension. Chunks flagged as gender-expressive receive a direction score on a Likert scale ranging from strongly feminine (-3) to strongly masculine ($+3$), while chunks flagged as political receive an analogous ideology score from strongly liberal (-3) to strongly conservative ($+3$).

We operationalize gender expression and ideological lean in our main analysis as ternary direction scores (-1 = feminine/liberal, 0 = neutral, $+1$ = masculine/conservative) rather than retaining the full 7-point Likert intensity scale used in the raw LLM output. This choice is motivated both empirically and theoretically. Empirically, human–LLM agreement is substantially higher on the directional classification than on the granular Likert scale where raters, both human and LLMs, reliably agree on which direction a chunk leans, but disagree on how strongly. The Likert-level disagreements are almost entirely ordinal-neighbor errors (e.g., “moderately conservative” versus “slightly conservative”) rather than directional inversions (see Appendix Section G and H on validation). This pattern indicates that intensity distinctions within a direction carry low intersubjective reliability and therefore we lean more on directional lean rather than intensity given the lean. Theoretically, the quantity of interest for our research question is directional exposure or whether listeners are immersed in masculine or conservative content. Collapsing to the ternary preserves the directional information where human to human and human to machine judgment converge, while discarding

²⁰In Appendix Section J we detail the importance of definitions in the gating mechanism (specifically politics detection) and address how this impacts downstream analyses.

within-direction intensity distinctions where they do not.

Episode-level scores are computed as word-count-weighted means across appropriate chunks in the episode. We weight by length of statements to reflect not just the lean of the statement or strength of lean of the statement on its own, but to also reflect the length at which it is addressed.²¹ The gender expression score averages the gender behaviors and gender topics scores. We then construct a net gender index for the episode which is the difference between the word-count-weighted share of chunks that are masculine (combined score > 0) and the word-count-weighted share of chunks that are feminine (combined score < 0), producing a measure scaled from $[-1, 1]$. The net gender index is then blended with a fixed value representing the podcast host's gender, weighted 90 percent to the transcript-derived index and 10 percent to the host value. Host gender enters as $+1$ for a male host, -1 for a female host, and 0 for a mixed or unidentified host, and was coded by research assistants directly from each podcast's own website, a coding validated across coders.

The ideology score is computed analogously but restricted to politically flagged chunks only. Specifically, the net ideology index is defined as the word-count-weighted share of conservative chunks minus the word-count-weighted share of liberal chunks among political chunks, and is undefined for episodes with no political content. Podcast-level scores are calculated as weighted means of the episode-level net indices. Ideology scores weight episodes by their total political chunk word count, reflecting how much politically informative content each episode contributes. Gender expression scores weight episodes by their total word count, since gender expression is present across most speech rather than only flagged segments.

4.3 Consumption Data from Edison Research

We obtained audience data from EPM in two different forms: "show profiles" for audience demographics for our full 276 podcast list; and an abbreviated individual-level survey dataset

²¹One could reasonably argue that word count weighting may overinflate weakly leaned statements that are long; however, a strongly leaned statement that is long should factor more into the overall episode score; therefore, we felt word count weighting was the most appropriate operationalization. We also tested weighting by time duration, and word count weighting and duration of speech produced similar results.

for the respondents Edison asked vote choice questions for in 2024. EPM conducts approximately 20,000 interviews per year of weekly podcast listeners aged 13 and older, with about 5,000 collected per quarter, in both English and Spanish. The show profiles are percentages of demographic groups that follow each podcast and are estimated by Edison from the individual level survey data. Our show profile estimates and individual level estimates are limited to the voting age population in their sample (omitting those under 18). The main variables available in both the show profiles and individual-level data include demographic audience breakdowns by age, gender, race, political party, employment status, education, income, and preferred podcast service platform.

The show profile reports the percentage of the podcast's audience in each demographic category, and the categories within a dimension sum to one hundred percent of the audience. A profile records, for instance, the percentage of a podcast's audience that is men and the percentage that is African American. These are marginal shares for each dimension on its own rather than a joint cross-tabulation, so we observe the share of an audience that is men and, separately, the share that is African American. Each profile also carries an estimated audience size for the podcast. We use the show profiles of the full 276 podcast sample to articulate ideological exposures across groups from our transcript estimates, as well as things such as how our measures of gender expression tracks the share of men or women in the audience of a podcast.

We use the individual level survey data to show how ideological exposure is related to vote intention for the 129 non-political podcasts for which we have exposure metrics and for which EPM has vote intention responses. In this sample, we have 3,544 respondents who answered vote intention questions in 2024 prior to the election. While the EPM survey is explicitly a sample of podcast listeners, they can be weighted to mimic a nationally representative sample by age, gender, and ethnicity using Edison's annual The Infinite Dial study, a mixed-mode survey combining telephone and online interviews of over 5,000 respondents.

4.4 Nationally Representative Survey Data

Lastly, we feature results from an original panel survey conducted by YouGov featuring 1,167 U.S. respondents who participated in the 2024 post-election wave between 01/02/2025 and 02/10/2025, and who participated in previous waves in 2016 and 2020 and reported vote choice during those waves. We asked respondents if they listen(ed) to any of the following podcasts in the last three months which featured a Trump or Harris interview: *Call Her Daddy*, *The Joe Rogan Experience*, *Club Shay Shay*, *Full Send Podcast*, *This Past Weekend w/ Theo Von*, *Unlocking Us with Brené Brown*, and *Flagrant Podcast*. We then use that to build a binary measure of Rogan listenership pre-election and model the probability of voting for Trump conditional on listening to Rogan prior to the election. We fit additional models for listening to any Trump appearance podcast (*The Joe Rogan Experience*, *Full Send Podcast*, *This Past Weekend w/ Theo Von*, and *Flagrant*) and vote, and any Harris appearance (*Call Her Daddy*, *Club Shay Shay*, and *Unlocking Us with Brené Brown*) and vote. The whole sample for the post-election wave was 2,422 individuals, but we limited our sample to individuals for whom we have their vote intention from previous survey cycles leaving a final sample of 1,167.

We acknowledge that selection bias could pose a clear challenge to testing our theories on how podcast exposure relates to vote choice. Men predisposed to conservatism may seek out masculine podcasts because both their podcast preferences and their political preferences stem from underlying gendered and ideological dispositions. Distinguishing selection from persuasion in observational data is difficult. We control for selection in two different ways detailed in the individual level results section. Empirically, we first control for partisanship in all models (both EPM and YouGov), following the approach developed in the talk radio literature (Barker, 1999, 2002). In our individual level YouGov data, we can impose a stricter selection test by controlling for previous vote for Trump alongside partisanship. Theoretically the argument we make is not that masculine podcasts uniquely cause conservative voting, but that they provide a site where latent conservative dispositions can be activated and

reinforced in the absence of a saturation of explicitly political content, and where candidates can reach voters sorted by gender expression rather than by partisanship.

5 Describing the Podcast Ecosystem and Evaluating its Political Impacts

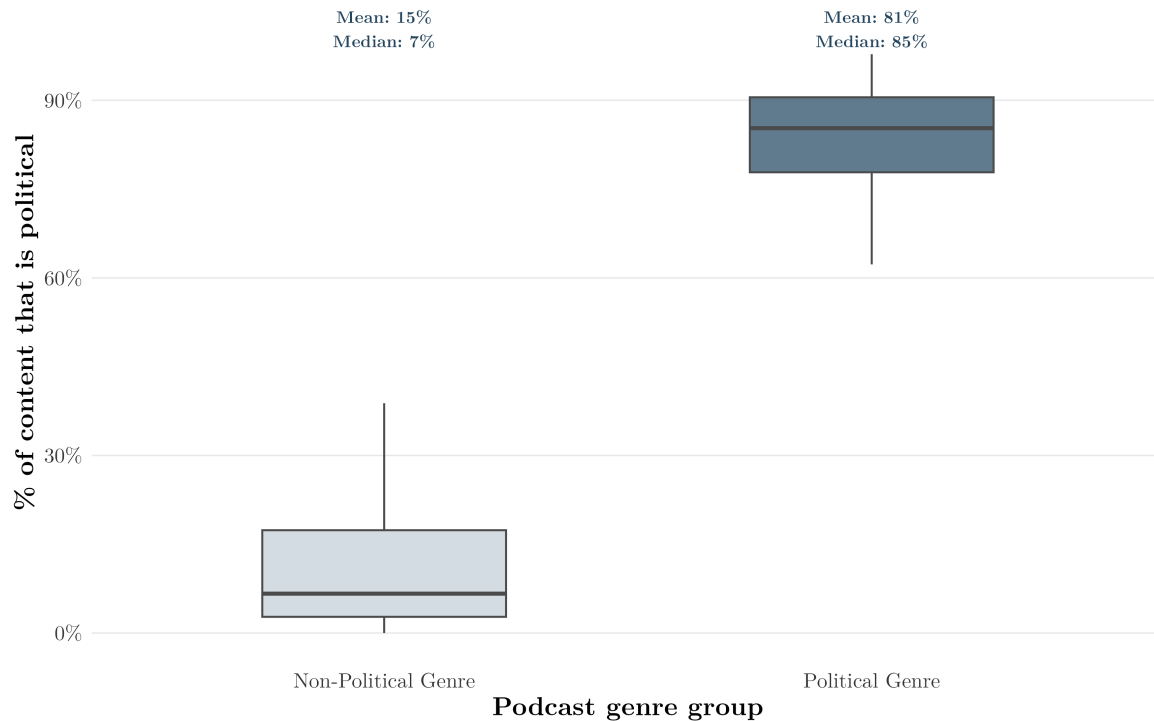
Given the novelty of podcast data to the study of American politics, we first detail exactly how much politics is in the top podcasts in the ecosystem. Figure 1 shows the distribution of podcast-level political content by political and non-political podcast genres where each box summarizes the distribution of values across podcasts within that genre group. The y-axis measures the average percent of a given episode’s content that was classified as political, defined as the number of chunks coded as political divided by the total number of chunks within each podcast’s episodes, and then averaged to the podcast level.

In political genre podcasts, the average percent of utterances in an episode that are about politics is 81% whereas in non-political podcasts the average amount of statements per episode about politics is 15%. The median share of politics statements in an episode of a non-political genre podcast is 7%, which we believe is a more accurate reflection of how much politics comes up in non-political spaces as there are some non-political podcasts that discuss politics a great deal driving the average score upwards (e.g., *Rachel Maddow Presents: Ultra*, *The Rest is History*, and *American History Tellers*, narrative history podcasts whose episodes frequently center on historical political events).²²

We highlight that while political-genre podcasts contain mostly politics, even non-political podcasts contain enough politics in them to bring exposure to an audience not tuning in for the main purpose of consuming political content. Figure 2 shows the ideological composition

²²Narrative history podcasts differ from explicitly political commentary in orientation, not topic. A show like *Ultra* covers an episode with a settled historical outcome, functioning as retrospective storytelling rather than commentary on live political stakes, closer to a History Channel documentary than a news broadcast. Political-genre shows are organized around unresolved political conflict in the present, where the point is persuading listeners on a question that’s still open.

Figure 1: Average Share of Political Content Across Podcast Genres.



Note: Boxes represent the distribution of share of episode that is political between non-political and political genre podcasts as determined by their self-identified genre tags. Mean and medians featured in text above boxplots, line in boxplot is median.

of episodes with political content detected across political and non-political genre groups. Of the 36,659 episodes in our sample, 5,354 (14.6%) contained no detectable political content and are excluded from this figure.²³ Each stacked bar represents the share of politically scored episodes in that genre group classified as liberal, moderate or mixed, or conservative (as an aggregate of their chunk level score lean). The moderate or mixed category captures episodes with no net ideological direction. A zero score can reflect either relatively neutral or descriptive language, such as news-like delivery, or a combination of liberal and conservative language that balances out overall. The vast majority of what is in the moderate/mixed category is content that is about politics, but has no discernible political lean.

Figure 2 shows that among non-political episodes with political content, the largest share

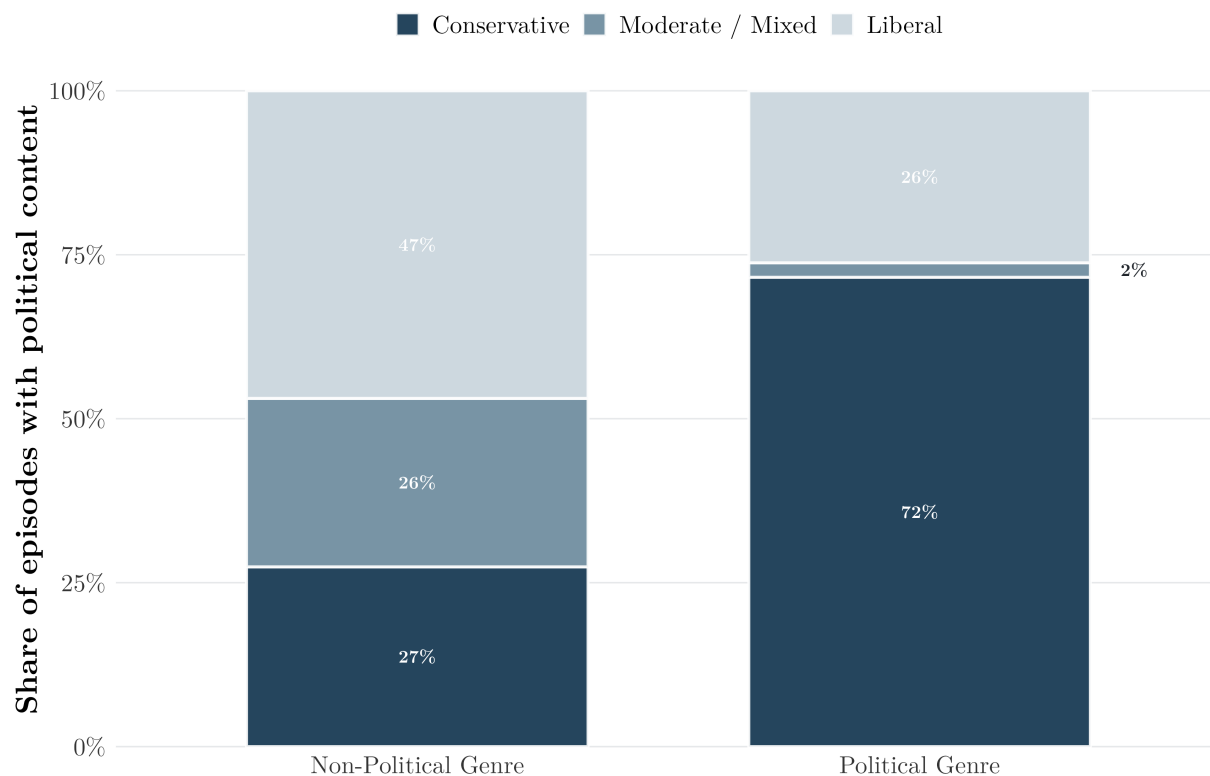
²³These are concentrated in non-political genres, where 22.5% of episodes had no political content detected compared to just 0.4% in political genres.

leans liberal (47%), followed by conservative (27%) and moderate or mixed content (26%). In contrast, the political podcast space is dominated by conservative content: 72% of episodes in political genres exhibit a conservative lean.

Taken together, these patterns suggest that assessments of ideological dominance in top podcasts depend on whether the podcast sells itself as overtly political or not. While conservative content dominates within explicitly political podcasts, liberal content is more prevalent across the broader ecosystem once non-political genres are included.

This distinction becomes clearer when comparing the number of podcasts and total output. Across the most popular political *and* non-political podcasts, liberal-leaning podcasts are more numerous and more prolific in aggregate, accounting for 192 podcasts and 19,842 episodes, compared to 79 conservative-leaning podcasts producing 16,812 episodes. This

Figure 2: Directional Ideology Composition by Genre Group



Note: Figure shows the ideological lean of politically scored episodes in each genre group (non-political vs political). Moderate/mixed reflects neutral delivery of political content or an equal combination of liberal and conservative commentary.

pattern is driven largely by the non-political sector, where liberal-leaning podcasts substantially outnumber conservative-leaning ones (173 vs. 60) and produce roughly twice as many episodes (15,944 vs. 7,657). The political subset, however, exhibits a different pattern. The number of liberal and conservative-leaning podcasts is exactly equal (19 vs. 19), but conservative political podcasts generate substantially more content (9,155 vs. 3,898 episodes). In other words, liberals occupy more of the overall top podcast landscape, but conservatives are markedly more prolific within explicitly political podcasting.

5.1 Candidate Strategy

Figure 3 plots the gender expression and ideology for each podcast in our sample. This includes both political and non-political podcasts. The horizontal axis measures the Net Gender Index, defined as the word-count-weighted share of masculine-coded chunks minus the share of feminine-coded chunks, where each chunk’s gender coding reflects the average of two dimensions: speech behavior style and topic association, blended with a small weight for the host’s self-identified gender as a structural anchor (Section 2.2). Positive values indicate predominantly masculine expression, and negative values indicate predominantly feminine expression. The vertical axis measures the Net Ideology Index, defined as the share of conservative-coded chunks minus the share of liberal-coded chunks among politically flagged content only (weighted by word count of political chunks), where positive values indicate a conservative lean and negative values indicate a liberal lean. Both indices are bounded on $[-1, 1]$. Dot size reflects estimated weekly audience size and color represents the average share of each episode devoted to political discussion. We additionally feature a linear regression trend line and a locally estimated scatterplot smoothing line (LOESS) to demonstrate the strength of the correlation. Both lines are weighted by audience size.

The figure reveals a positive correlation between masculine expression and conservative ideology across the podcast ecosystem, consistent with H1. As podcasts become more masculine, they are also more likely to align with conservative ideology. Conversely, more feminine

podcasts are much more likely to be liberal. We observe this at both the podcast and episode level (the plot features the podcast level because of the sheer number of episodes). This supports H1 and suggests that the gender and ideology dimensions of podcast content are related as we expect.

Figure 3: The Relationship Between Podcast Gender Expression and Political Ideology



Note: Each point is the average score on gender expression and ideology scores for a given podcast. Colors reflect the average percent of an episode devoted to political discussion. LOESS and linear regression trend are weighted by audience size.

In terms of the overall podcast ecosystem seen in Figure 3 we observe a few important trends. The majority of the most popular podcasts skew slightly masculine in both topics and gendered language characteristics. Despite the majority being ostensibly entertainment,

most podcasts at least occasionally discuss political topics, and convey an ideological stance. We see a clear cluster in the conservative masculine upper right quadrant that talk about politics densely (darker color) and produce a lot of content in terms of number of episodes. However, as previously alluded to, when you consider both political and non-political podcasts there are quite a few liberal skewing podcasts that do produce a sizable amount of political content. It is important to note that just about all conservative podcasts are heavily masculine, while masculinity itself spans the ideological spectrum.

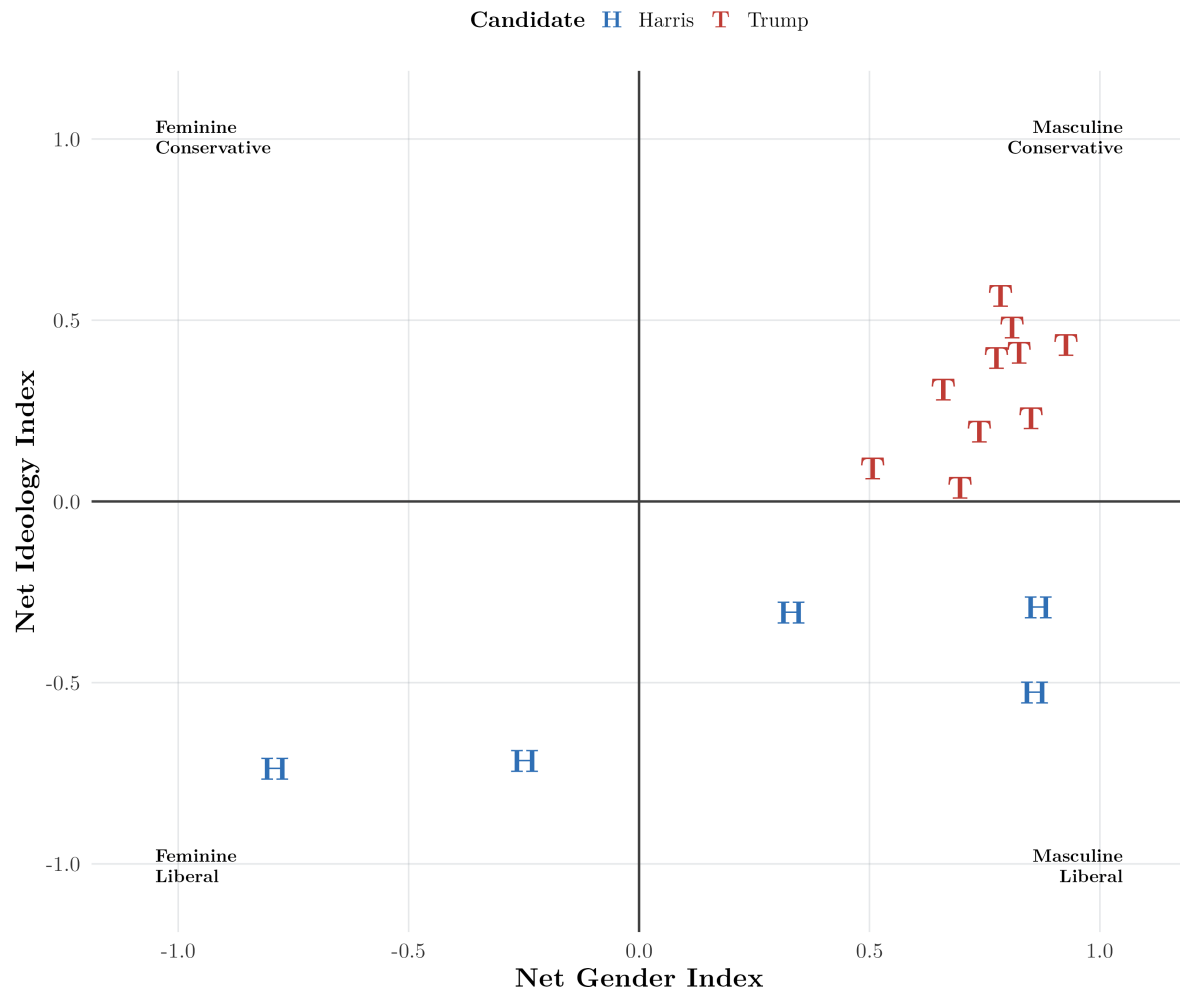
Next, we evaluate candidate strategy (H2) by focusing on non-political podcasts visited by Harris and Trump, and evaluate whether the ideological or gendered features of these podcasts are more predictive of their selections. We evaluate all podcasts in our sample on which either Trump or Harris made an appearance in 2024. We identified and were able to collect data for 16 Trump interviews and 5 Harris interviews, which we then subset to non-political genre appearances.²⁴

Figure 4 displays these results where we plot the same gender and ideological averages specifically for the candidate interviews. Trump also appeared on six overtly political genre podcasts not shown in this figure (The Ben Shapiro Show, The Dan Bongino Show, The Glenn Beck Program, The Clay Travis and Buck Sexton Show, The Tucker Carlson Show, and Timcast IRL), which are excluded to keep the comparison focused on non-political podcasts. The blue H's are Harris interviews and the red T's are Trump interviews. We find that Trump focused on low-political lean share masculine podcasts. Harris consistently appeared on ideologically liberal podcasts regardless of their gender expression. Notably, all five Harris appearances were on non-political genre podcasts.

While the Trump appearances leaned conservative when they did talk about politics, we show in Appendix Figure A6 these podcasts featured a wide variety of political content beyond just conservative conversation. Other survey evidence reaches a similar conclusion

²⁴These represent all candidate appearances across podcasts in our sample with publicly available RSS feeds, which are required for audio download and transcription. Appearances on podcasts that distribute exclusively through YouTube, streaming, or without an RSS feed are not captured (ex: Adin Ross live stream with Trump or Harris's Howard Stern radio appearance).

Figure 4: Gender Expression and Political Ideology of Presidential Candidate Appearances



Note: Red T's denote non-political genre Trump interview appearances and blue H's non-political Harris interview appearances plotted for their average gender expression and ideology across episodes.

about his audience, where Rogan's listeners cohere around shared cultural orientations rather than conventional partisan alignment (Stecula et al., 2025). This supports our content-level finding that these podcasts are not simply conservative echo chambers.

We support this with analysis of the partisan composition of the audience in Appendix Section B, where across the ten non-political genre podcasts Trump appeared on, only 38% of the average podcast audience identifies as Republican, with 21% identifying as Democrat and 32% as Independents. The majority of this audience is not already in the Republican

coalition, consistent with the Trump campaign selecting on gender rather than ideology in these appearances. The Harris appearances present a different pattern. They span the gender expression spectrum but lean uniformly liberal, and the podcasts targeted had audiences of primarily Democrats with only a minority Independent or Republican (Figure A2). Notably, the three masculine Harris appearances were among the most popular Black podcasts in the top podcast sample. Together, this is consistent with a Trump strategy to target persuadable masculine voters and a Harris strategy to mobilize the existing Democratic base, including young women and Black voters, rather than persuade new ones.

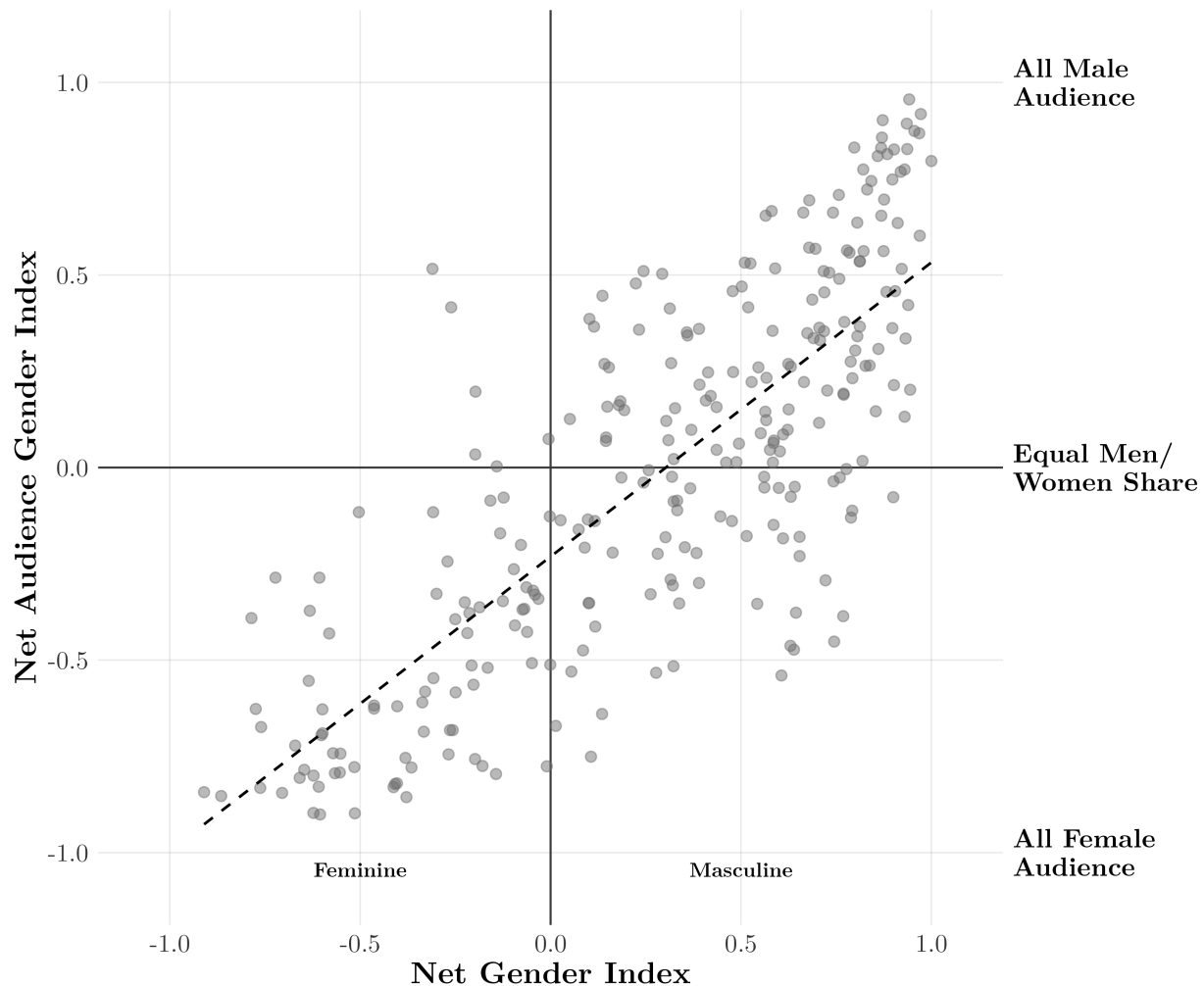
Overall, Figure 4 supports H2 in terms of the Republican candidate, but shows that the Democratic candidate appeared to select podcasts based on ideology and not gender.

5.2 Consumption Behavior

Next, we evaluate our hypothesis that podcasts with more masculine gender expression will have audiences that are disproportionately male (H3) by testing whether the gender composition of podcast audiences tracks the gendered expression of their content. In Figure 5 we display the relationship between audience gender composition and the average gender expression score of the podcast to test if masculine-coded podcasts will have audiences that are disproportionately male. We find that, indeed, the audience demographics mirror the gender scores we attain for each podcast where men consume more masculine content and women consume more feminine content. The more masculine the podcast is, the higher percent of men in their audience (and vice versa). Our findings thus provide empirical support for H3 and show that candidates can select on masculinity or femininity to find audiences of that gender group.

We now pivot to testing our fourth hypothesis which is that individuals exposed to more conservative content on non-political podcasts were, *ceteris-paribus*, more likely to vote (or intend to vote) for Trump. Combining our content scores with audience demographic data, we estimate the gender gap in conservative podcast exposure for different age groups (people

Figure 5: Podcast Gender Expression and Audience Composition



Note: The figure compares the gender composition of each podcast’s audience (y-axis) with the gender-expression score of its content (x-axis).

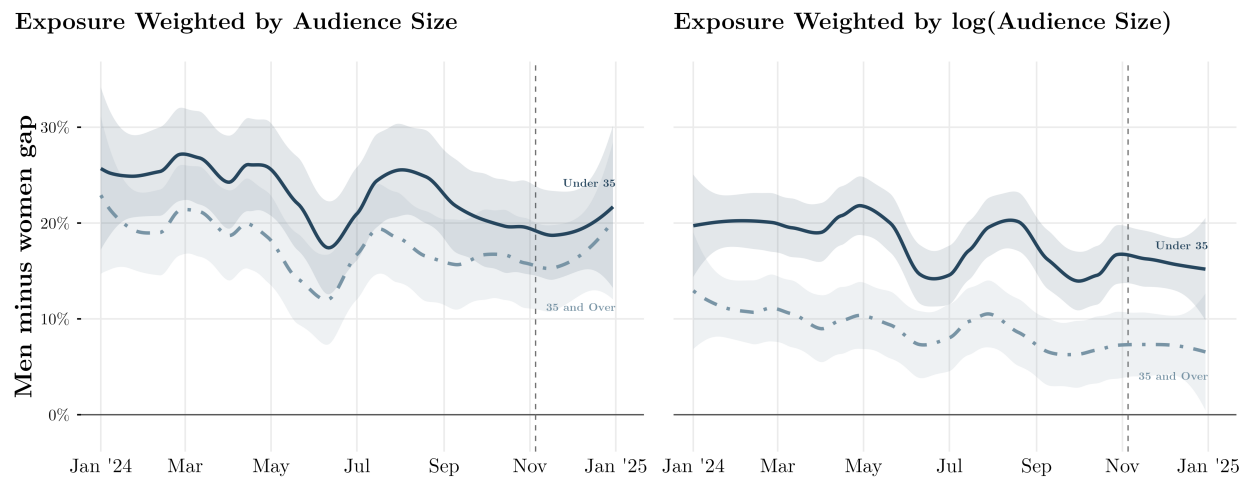
under 35 and people 35 or over) over the course of 2024 for non-political podcasts to capture incidental exposure. These results are presented in Figure 6.

Figure 6 plots the weekly gender gap in conservative podcast exposure for under-35 and 35+ listeners from January 2024 through early January 2025 under two weighting schemes.²⁵ Each week’s gap is the difference between the share of conservative episodes heard by men and the share heard by women within each age group. An episode is classified as conservative-

²⁵A five-age-group version of this figure appears in Appendix Figure A3. The five-age-group version of this analysis shows that the two youngest cohorts (18–24 and 25–34) cluster together above the three older cohorts, so we collapse age into “young” (18–34) and “older” (35 and over) here and in the individual-level analyses that follow.

leaning if the word-count-weighted share of conservative-coded political chunks exceeds the share of liberal-coded political chunks. Episodes must have at least 5% political content to be included. The left panel weights each podcast by its raw audience size so that each listener counts equally; the right panel weights by $\log(\text{audience size})$, which reduces the dominance of the largest podcasts and surfaces patterns across the broader ecosystem.²⁶

Figure 6: Gender Gaps in Conservative Podcast Exposure by Age Group



Note: The figure shows men’s conservative podcast exposure minus women’s exposure within each age group from January 2024 to January 2025. The sample includes only podcasts classified in non-political genres. The left panel weights podcasts by raw audience size, while the right panel weights podcasts by the logarithm of audience size.

Peaks indicate weeks where the episodes reaching men skewed more conservative relative to what was reaching women. A trough means the gap narrowed. Under raw audience weighting, the trends are dominated by the Joe Rogan Experience, whose weekly audience is 3.2 times larger than the next biggest podcast, Crime Junkie, and 33 times larger than the average podcast in the rest of the sample. The log specification reduces this dominance and shows that smaller podcasts drifted conservative in a meaningful way over the same period. The two specifications indicate that the conservative exposure gap is not the artifact of a single overly large podcast. In both weighting specifications, young men under 35 show

²⁶We weight to ensure we are articulating not just the gender gap in conservative content during the period, but also the relative reach of that content across age gender groups. Without accounting for how many people listen to each podcast, a podcast reaching 10 listeners would count as much as one reaching 10 million. Weighting by audience size therefore reflects what listeners are actually hearing across the population, not just the average ideological lean of podcasts regardless of their reach.

a persistently larger gender exposure gap than the 35+ group throughout the pre-election period. This means that young men were exposed to more conservative content in the run-up to the election than young women were, and the size of this gap was larger than the gap between older men and women's exposure.

To formally compare the two age groups, we run a paired t -test on the weekly gap values within each group over the pre-election period (January 2024 through Election Day), pairing by week since the two age groups' weekly gaps are observed for the same calendar weeks and are strongly correlated. The under-35 gap in consumption of conservative podcast content by gender is significantly larger than the 35+ gap in consumption of conservative content in both the raw audience specification ($p < 0.001$), and the log specification ($p < 0.001$).

Appendix Table A6 identifies which non-political podcasts contribute most to the aggregate gap under each weighting scheme. Beyond *The Joe Rogan Experience* we highlight the relevance of shows such as the *Full Send Podcast*, *Impulsive with Logan Paul*, and *This Past Weekend w/ Theo Von* in contributing to shifting conservative exposure. Each of these featured an interview with Donald Trump, and beyond talking about politics only occasionally, share a consistent thread of irreverent, non-politically-correct humor, jokes and commentary on gender, identity, or culture-war flashpoints delivered without much concern for giving offense. This is consistent with our broader argument that masculine-coded style itself is compatible with conservative content, even in episodes that are not explicitly about policy or elections. We now pivot to connect this conservative content exposure gender gap to observational evidence of voting patterns in the next section.

5.3 Connecting Exposure to Vote Intention and Vote Choice

We first detail the modeling strategy and variable construction for both the EPM and YouGov samples before testing H4, whether conservative content exposure is associated with higher support for Trump after controlling for known political predispositions and demographic characteristics associated with such predispositions.

5.3.1 Edison Podcast Metrics Individual-Level Listener Data Models

Dependent Variable The outcome variable Y_i is a binary indicator of two-party Trump vote intention for respondent i , drawn from the EPM survey. Respondents who report they would “definitely” or “probably” vote for Trump are coded $Y_i = 1$ and those who report they would “definitely” or “probably” vote for Harris (or Biden in earlier survey waves) are coded $Y_i = 0$.²⁷ Models are estimated as survey-weighted logistic regression using EPM survey weights.

Content Exposure A unique content exposure measure is constructed for each respondent by linking each listener’s reported podcast diet to our episode-level content scores and accounting for when the respondent was surveyed and how much they reported listening.

For respondent i , let d_i denote their interview date and let $\mathcal{S}_i$ denote the set of non-political genre podcasts respondent i reports listening to in the Edison survey. Restricting to non-political genre podcasts is a partial guard against selection on predisposition. Audiences of entertainment podcasts are drawn to podcasts for reasons unrelated to politics and are therefore less ideologically sorted, reducing the degree to which selection into conservative content can explain the estimated relationship.

For each podcast $s \in \mathcal{S}_i$, let $\mathcal{E}_{si}$ denote the set of episodes of podcast s with detected political content published between January 1, 2024 and $t_i = \min(d_i, \text{November 5, 2024})$. For podcasts with at least one such episode, the podcast-level lean is the mean episode-level conservative lean over this respondent-specific exposure window:

$$\bar{c}_{si} = \frac{1}{|\mathcal{E}_{si}|} \sum_{e \in \mathcal{E}_{si}} (\hat{p}_e^{\text{con}} - \hat{p}_e^{\text{lib}}), \quad |\mathcal{E}_{si}| > 0,$$

where $\hat{p}_e^{\text{con}}$ and $\hat{p}_e^{\text{lib}}$ are the chunk-weighted shares of conservative and liberal content among the politically flagged chunks of episode e . Let $\mathcal{S}_i^+ = \{s \in \mathcal{S}_i : |\mathcal{E}_{si}| > 0\}$ denote the subset

²⁷Respondents who are undecided or indicate they will not vote are excluded from the analytic sample. EPM did not ask post-election vote choice; pre-election vote intention is the closest available measure.

of respondent i 's reported non-political genre podcasts with at least one politically flagged episode during the exposure window. The respondent's conservative exposure averages those podcast leans across this politically observed portion of their diet:

$$C_i = \frac{1}{|\mathcal{S}_i^+|} \sum_{s \in \mathcal{S}_i^+} \bar{c}_{si} \in [-1, 1].$$

Positive values of C_i indicate a net conservative podcast diet and negative values indicate a net liberal diet.

The key predictor in the models is the conservative listening index:

$$D_i = C_i \times h_i \times w_i,$$

where h_i is respondent i 's self-reported weekly podcast listening hours²⁸ and w_i is the number of weeks elapsed from January 1, 2024 to t_i . The product $h_i \times w_i$ approximates intensity and scale of conservative exposure during the period, so D_i scales the directional lean of the diet by how much the respondent likely listened. The sign of D_i inherits the liberal-to-conservative direction of C_i while its magnitude reflects cumulative exposure. All models include $\log(1+h_i)$ as a separate additive control, so the coefficient on D_i captures cumulative directional exposure net of overall weekly podcast listening volume.

Controls and Model We include the following controls in all models. Age is divided into two groups following the age-based listenership patterns in Figure 6, with respondents 34 and under coded as young and those 35 and older coded as older. Gender is coded as a binary indicator where men are 1 and women are 0; respondents identifying as non-binary are omitted due to data scarcity. Race is included as a set of indicators for Black and Hispanic respondents with white respondents as the reference group. Party identification contrasts

²⁸Weekly listening hours are capped at the 99th percentile of the sample distribution to limit the influence of implausibly large self-reports. Listening hours are accounted for in the index and separately controlled in the model to ensure heavy listeners aren't driving findings, results are unchanged whether listening hours are included or not included in the index (no multi-collinearity issue).

Independents and Republicans against Democrats as the reference group. Education is a binary indicator for whether a respondent holds a bachelor's degree or above. Income is divided into quartiles. We also include logged weekly listening hours to account for overall podcast consumption on its own and survey wave fixed effects to absorb any common time trends across the data collection period.

We estimate a survey-weighted logistic regression interacting the conservative listening index with party identification and including a gender-by-age interaction as an additive control. This allows the association between the conservative listening index and Trump vote intention to vary across Democrats, Independents, and Republicans while also estimating whether young men vote differently from other gender-age groups holding exposure constant. Results are reported in Figure 7 and Appendix Tables A1 and A2. Figure 7 reports average marginal effects of a one standard deviation increase in the conservative listening index on the probability of Trump vote intention, estimated separately by party identification and by gender-by-age group from models that interact the index with each grouping variable in turn.²⁹

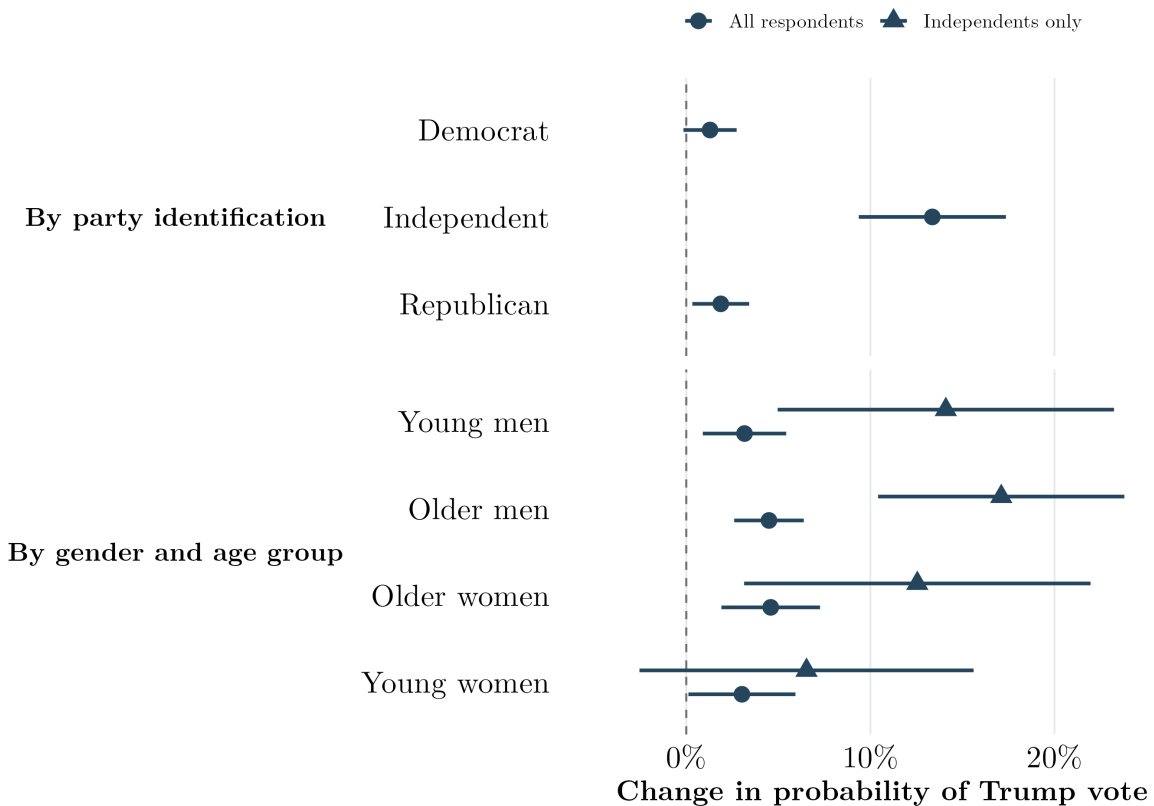
5.3.2 EPM Individual-Level Listener Data Results

Figure 7 presents results from the EPM individual-level listener data average marginal effects (AMEs) from models featured in Appendix Tables A1 and A2 with full controls. We feature the AME of a one standard deviation increase in the conservative listening index on the probability of Trump vote intention, estimated separately by party identification and by gender-by-age group. To contextualize what one standard deviation means for young men, it is roughly the difference between a typical listener with about four hours of podcasts a week, on a diet that leans only mildly conservative to a heavy listener who spends around ten hours a week with content leaning as conservative as *The Joe Rogan Experience* averages. First with

²⁹We also estimated a single combined model interacting the conservative listening index with both party identification and gender-by-age group simultaneously. Average marginal effects were substantively identical across all groups. For ease of presentation we present results from the two-model specification.

regards to party, we see the association between conservative podcast exposure and Trump vote intention is concentrated among Independents, who show the largest positive association of any party group. This is consistent with the incidental exposure mechanism operating most strongly among listeners who are not already sorted into the partisan media ecosystem and therefore have fewer countervailing considerations when they encounter conservative content. The association is substantially smaller for already-sorted partisans, as expected given that Democrats and Republicans are close to their respective floors and ceilings on Trump vote intention regardless of podcast exposure.

Figure 7: Conservative Podcast Exposure and Trump Vote Intention in EPM Survey



Note: The figure presents estimated relationships between conservative podcast exposure and intention to vote for Donald Trump among podcast listeners from logistic regression models. Circles show estimates from the full sample, while triangles show estimates from the same models re-estimated among Independents only.

Across all gender-by-age groups increases in conservative exposure in non-political spaces are associated with higher Trump intent. The gender-by-age-group panel also shows esti-

mates from the same model re-estimated on Independents only (triangles), since the by-party panel establishes that Independents are the group among whom the dose effect is substantive. Among Independents, the effects are roughly three to four and a half times larger for men and nearly three times larger for older women, while young women's association drops to non-significant. Within the persuadable subset of listeners, men show consistent positive associations across age groups while young women do not.³⁰

The AME movement across multiple age and gender groups is consistent with the theoretical mechanism about masculinity as a pathway. Winter (2010) finds that Americans associate the Republican Party with traits including active, independent, and decisive at the implicit level. The same study also reveals that these trait associations are held broadly rather than exclusively by men, so masculine-coded conservative content may activate Republican-aligned schemas in any listener, not only those who identify as men. A strategy seemingly targeted at masculine podcasts, whose audiences skew toward young men and Independents, therefore may have activated these cognitive pathways more broadly than intended. Other gender and age groups present in these audiences were also exposed to conservative content and show similar associations between that exposure and Trump vote intention, suggesting the persuasive pathway is not exclusive to young men. What differs across groups is not responsiveness per unit of conservative content but the volume of that content encountered by each group.

Figure 7 reveals that conservative exposure is similarly associated with Trump vote intention per unit across gender and age groups. However, Figure 6 shows that these groups were not equally exposed to conservative content. To further illustrate this point with the smaller EPM vote intention subset, Table 1 presents the share of podcasts in each group's podcast diet whose political episodes lean majority-conservative, and what that translates to in weekly reach. Among EPM-vote intent tracked non-political podcasts, 54.7% of the

³⁰We also estimated the same models subset for Democrats and Republicans. The results were consistent with results reported in the top of the figure where Republican and Democrat coefficients were either indistinguishable from zero or very small.

podcasts in young men’s diet are net-conservative, compared to 49.3% for older men, 34.8% for older women, and 25.6% for young women. The 29-percentage-point gap between young men and young women is the largest divide. Importantly, the EPM subset list likely understates young men’s true conservative exposure. Podcasts with heavily young male audiences, such as *Bussin’ With the Boys*, did not have enough respondents who were asked vote-choice questions to be included in the analysis.

Table 1: Conservative podcast exposure by demographic group

Group	Conservative podcast share (%)	95% CI	Weekly Audience (M)
Young men	54.7	[51.5, 57.8]	13.6
Older men	49.3	[46.3, 52.3]	14.2
Older women	34.8	[31.7, 37.9]	6.4
Young women	25.6	[22.4, 28.9]	5.9

Note: Conservative podcast share is the percentage of podcasts in each group’s EPM diet that lean net-conservative, averaged across respondents and weighted by EPM respondent weight. Weekly reach is the sum of Edison audience size estimates across each net-conservative show in the group’s diet (millions); a listener who follows more than one such show is counted once per show, so this is aggregate show-level reach/exposures, not deduplicated unique weekly audience.

Among net-conservative non-political podcasts with Edison audience estimates, we estimate 13.6 million weekly young male listeners and 5.9 million weekly young female listeners, a gap of roughly *8 million people*.³¹ Older men’s weekly reach (14.2 million) exceeds young men’s primarily because *The Joe Rogan Experience* draws a larger older male audience (8.0 million) than young male audience (7.0 million); the conservative podcast share column reflects this distinction, with young men’s overall diet more consistently conservative than older men’s despite similar raw reach. These differences show that young men and young women inhabited meaningfully different conservative content environments through their podcast consumption in the months before the 2024 election.

Figure 8 shows the AME results in vote probability terms by asking what would happen to each group’s predicted Trump support if their conservative listening index were set to

³¹This figure sums each net-conservative show’s Edison audience size estimate across every such show in the group’s diet. A listener who follows more than one such show is counted once per show, so this reflects aggregate show-level reach/exposures rather than deduplicated unique weekly audience.

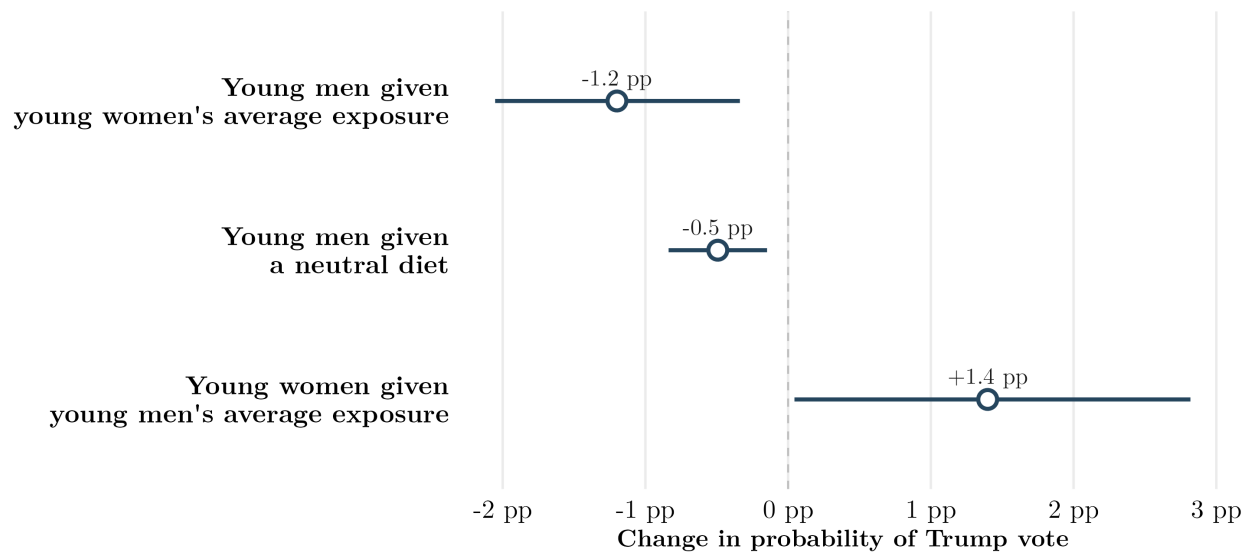
a different level, holding all other covariates fixed. We report three scenarios: young men given the average diet of young women, young men given a neutral diet (conservative index set to zero), and young women given the average diet of young men. In each case, predicted probabilities are averaged within the group using survey weights and intervals come from 4,000 draws from the coefficient distribution. If young men consumed the same conservative podcast diet as young women, their predicted Trump support falls by 1.2 percentage points. The symmetric counterfactual — raising young women to young men’s exposure — moves their support for Trump upward by 1.4 percentage points.

While this is a meaningful shift, it is modest relative to the overall size of the youth gender gap which widened to 16 points in 2024 (up between 5 and 6 points from 2020), indicating that conservative podcast exposure alone is unlikely to account for the full magnitude of that shift. We return to the original question that motivated this paper, which was: did podcasts help Trump win young men? The evidence here suggests, partially. Young men were differentially exposed to conservative content through non-political podcasts, and that exposure is associated with higher predicted Trump support, but the association is modest enough that podcasts alone cannot account for the full 2024 shift in the youth gender gap. We turn next to an independent dataset, the YouGov panel, which lets us test this relationship against actual vote choice rather than intention, and net of respondents’ prior vote.

5.3.3 YouGov Panel: Nationally Representative Individual-Level Data

We now pivot to the nationally representative YouGov dataset which allows us to control for prior vote choice alongside partisanship, providing a stronger accounting for pre-existing political predispositions than the EPM data alone. We predict vote for Trump (where 1 is voting for Trump and 0 is voting for Harris) based on self-reported podcast consumption with the following controls: vote for Trump in 2020 (post-election 2020 vote choice from their 2020 panel response), age (continuous, calculated as 2024 minus birth year from time of survey); gender (binary where 1 is identifying as a woman); race (White/Black/Hispanic

Figure 8: Counterfactual Scenarios of Exposure on Trump Vote Probability



Note: The figure presents predicted changes in the probability of intending to vote for Donald Trump under alternative levels of conservative podcast exposure.

where the reference group is White); income quintile (respondent household income binned into five quintiles); college degree (a binary variable for has a Bachelor's degree or above); and party identification (Democrat/Republican/Independent where the reference group is Democrat).³²

In the main text we feature 2020 vote choice controls so we restrict the sample to the 1,167 of the 2,422 respondents we have vote choice for in both years. The main utility of this model is that it allows us to account more directly for selection effects beyond partisanship, which we cannot do with the EPM data. In particular, we observe respondents' 2020 vote choice contemporaneously, rather than relying on a 2024 retrospective report of how they voted in 2020.³³

³²We additionally test models conditioning on 2016 vote choice (reported immediately following the 2016 election) in addition to 2020 vote choice, and report the results in Appendix Table A3.

³³We started the panel in 2016, and measured respondents' 2016 vote choice from their 2016 survey responses. Including this measure did not change the results. We estimated separate models controlling for 2016 Trump vote, 2020 Trump vote, and both 2016 and 2020 Trump vote. Because the results were substantively unchanged across specifications, we report the model using the more recent 2020 vote measure.

5.3.4 YouGov Individual Level Results

Table 2 estimates the association between podcast listenership and 2024 Trump vote using weighted logistic regressions. Coefficients are shown as log-odds with standard errors in parentheses.³⁴

Column one estimates the Rogan association directly where listeners of *The Joe Rogan Experience* in the last three months have significantly higher log-odds of voting Trump than non-listeners net of all controls ($b = 1.743$, $SE = 0.565$, $p < .01$). Column two broadens the group to any podcast that hosted a Trump campaign appearance in 2024 (*The Joe Rogan Experience*, *Full Send Podcast*, *This Past Weekend with Theo Von*, and *Flagrant*) and finds a similar association ($b = 1.474$, $SE = 0.506$, $p < .01$).³⁵ Appendix Table A3 presents models across different prior-vote control specifications, confirming that the Rogan association is robust.³⁶ Column three estimates the analogous model for the three podcasts that hosted a Harris interview in the YouGov data: *Call Her Daddy*, *Club Shay Shay*, and *Unlocking Us with Brené Brown*. Harris-appearance podcast listeners show a positive but statistically insignificant association with Trump vote ($b = 0.569$, $SE = 0.729$, $p > .10$). The insignificant point estimate, conditioning on prior vote history, is consistent with Harris's podcast outreach reaching partisan audiences that had voted Democratic in prior elections, and were not likely to switch their vote, rather than reaching persuadable voters.

Substantively, these estimates suggest that exposure to Trump-appearance podcasts operates beyond Republican identification or prior Trump support. Even after accounting for

³⁴The positive coefficient on Black in columns one and two is a consequence of conditioning on 2020 Trump vote. After conditioning on prior vote, and fixed demographic characteristics are just measuring movement for the demographic group towards, or away from, Trump in 2024 relative to 2020. Thus the coefficient does not suggest Black respondents were more likely than White respondents to vote for Trump in 2024, but that they shifted more towards Trump in 2024 than Whites did. The coefficient reverts to the expected negative direction in the specification without any prior vote control (Appendix Table A3, column one).

³⁵We also estimated models for columns one and two that additionally control for Harris-appearance podcast listenership. The Rogan coefficient changes minimally ($b = 1.714$, $SE = 0.577$) and the Trump-appearance coefficient is likewise stable ($b = 1.441$, $SE = 0.519$), while the Harris coefficient shrinks toward zero in both combined specifications.

³⁶The smaller Trump-appearance podcasts produce noisier and less precisely estimated coefficients with the exception of *Andrew Schulz's Flagrant with Akaash Singh*.

respondents' 2020 Trump vote, listeners remain significantly more likely to vote Trump in 2024. These associations are statistically significant and robust, but modest in absolute size. Listening to Rogan or a Trump-appearance podcast is associated with a 6.2 and 5.1 percentage point average increase in predicted Trump vote probability, respectively.³⁷ These age-gender groups vary substantially in Rogan's audience with 41.7% of young men reporting listening in the last three months, compared to 23.5% of young women. To provide an additional counterfactual with the YouGov dataset, we calculate how young men's predicted probability of voting for Trump changes when we set their listening share to other age-gender groups' observed rates, specifically young women. If young men listened to Rogan at young women's rate, their predicted probability of voting Trump falls by 1.3 percentage points; and raising young women to young men's listening rate moves their predicted support upward by 1.6 percentage points. These results are strikingly similar to what we observe in Figure 8.

Overall, the Edison listener data and the YouGov panel both show observational evidence of a link between conservative podcast exposure and Trump vote intent and vote choice, consistent with H4. We note that much of this shift is based on differential exposure rather than differential association between listening and vote choice between age-gender groups, though we do not rule out differential association from the Edison data.

³⁷We additionally estimated Bayesian partial-pooling model in Appendix Table A5 to account for small group listener cells and provide some comparable estimates to the EPM counterfactual estimates. The results are substantively the same as the age-gender group first differences here. The estimated association between Rogan listenership and vote choice is similar in magnitude across sex-age groups, consistent with the pattern in the EPM analysis.

Table 2: Predicting 2024 Vote Choice by Candidate Podcast Appearances

	(1)	(2)	(3)
Rogan Listener	1.743** (0.565)		
Any Trump-appearance podcast		1.474** (0.506)	
Any Harris-appearance podcast			0.569 (0.729)
2020 Trump vote	5.268*** (0.494)	5.323*** (0.476)	5.429*** (0.514)
Age	0.001 (0.013)	0.001 (0.012)	-0.005 (0.013)
Woman	-0.451 (0.398)	-0.426 (0.381)	-0.522 (0.409)
Black	1.471* (0.609)	1.426* (0.588)	1.508* (0.626)
Hispanic	-0.556 (0.715)	-0.494 (0.690)	-0.200 (0.754)
Income quintile	-0.140 (0.159)	-0.130 (0.151)	-0.109 (0.161)
BA or higher	-0.159 (0.442)	-0.104 (0.426)	-0.077 (0.459)
Republican	4.030*** (0.611)	3.844*** (0.568)	3.827*** (0.613)
Independent	2.611*** (0.546)	2.536*** (0.517)	2.513*** (0.569)
N	1167	1167	1167
Majority-class baseline	53.5	53.5	53.5
Correctly classified	96.5	96.6	96.7
Increase (pp)	43.0	43.1	43.2
First difference (pp)	+6.2 pp	+5.1 pp	+1.9 pp

Log-odds coefficients, standard errors in parentheses. Outcome in all columns is Trump 2024 vote (1 = Trump, 0 = Harris), two-party voters only. (1) Rogan listener; (2) any Trump-appearance podcast; (3) any Harris-appearance podcast (negative = lower odds of voting Trump). First difference is the average change in predicted $\Pr(\text{Trump vote})$ for a listener versus an otherwise-identical non-listener, holding controls fixed. * $p < .05$, ** $p < .01$, *** $p < .001$.

6 Discussion

This paper provides evidence of gendered media spaces in the podcasting environment and shows that the gender-coded nature (level of masculinity or femininity) of podcast content is correlated with the political content that appears in both ostensibly political and non-political podcasts. These findings extend the incidental exposure literature by demonstrating that incidental exposure is not random; it is structured by the gendered architecture of entertainment media. Individuals who consume masculine-coded content are systematically more likely to encounter conservative political messaging, while those who consume feminine-coded content are more likely to encounter liberal messaging. We highlight this important and novel finding that gender is a structural feature of the podcast ecosystem which creates predictable pathways by which candidates can reach audiences who are not actively seeking political content but whose underlying interests are amenable to a particular ideological direction.

Our candidate strategy results suggest an important departure from canonical accounts of party asymmetry in targeting behavior. Grossmann and Hopkins (2016) show that the Republican Party tends to coalesce around ideology rather than targeting specific demographic groups, as Democrats do. We find that in the podcast context, the Trump campaign focused on podcasts that were slightly conservative in the aggregate, but often featured a variety of political ideologies. At best it suggests a weak ideological targeting pattern. The clustering on masculinity is much more prominent, and the partisan breakdown of the podcasts' audiences was not majority Republican (Figure A1). This suggests that the Trump campaign was focusing on reaching individuals who were not already ideologically sorted but who were culturally predisposed to be receptive to conservative messaging to *persuade* (Winter, 2010; Peck, 2025). Masculinity thus functioned as a pre-political signal for candidate outreach, one that allowed Republican appearances to reach beyond audiences that would be found in explicitly conservative spaces. The Harris campaign, by contrast, concentrated its appearances in ideologically congruent podcasts. In Figure A2 we show that Harris appearances

were in non-political venues that leaned liberal, but also that had predominantly Democrat audiences. This is more consistent with a mobilization strategy as opposed to a persuasion of the less predisposed.

We do find an empirical association between exposure to conservative content in non-political podcasts and vote for Trump. However, we offer a few important limitations to the current study. Our results are consistent with the idea that these media environments were consequential for young men and other groups, but we cannot provide a direct causal link between exposure and vote choice as we are working with observational data in both cases (EPM and YouGov). The observed associations *could* be the result of selection bias where individuals likely to vote for Trump choose to consume non-political podcasts that exposed them to conservative political content. Were we examining the association between political podcasts and vote-choice, we think this would be a major concern. Given that we are working with non-political podcasts, and that we condition on prior vote in one of our datasets — while we cannot rule this out, we think it is less likely to be driving our results. For the individual-level data, we observe that conservative exposure in EPM and Rogan listenership in the YouGov data are both associated with higher Trump support even after controlling for underlying partisanship and, in the YouGov data, previous vote. While a randomized design would be needed to establish a causal link, the consistency of the finding across independent data sources, methodologies, and after conditioning on the strongest known predictors of Trump vote is unlikely to be driven entirely by selection.

A notable limitation of our analysis concerns the racialized dimensions of this media ecosystem. Recent scholarship suggests that the gender gap among young voters may have been especially pronounced among young men of color, who shifted toward Republican identification at notable rates in 2024 (CIRCLE at Tufts University, 2024). Emerging work attributes these shifts in part to the role of sexism and the Black manosphere (Robertson and Tesler, 2024; Crowder, Slaughter and Greer, 2026). Our analysis cannot test these dynamics directly. Just as we examine masculine-coded media spaces broadly rather than the

manosphere specifically, we are not positioned to characterize racialized media ecosystems or the Black manosphere in particular. The top 0.01% of podcast consumption skews heavily White on both the production and consumption sides, rendering our sample poorly suited to identify the relationships of interest for that question. Equally important, the theoretical mechanisms through which gendered and racialized messaging intersect require more sustained development than we can offer here; Crowder, Slaughter and Greer (2026) provides a productive model for this work. We view the racialized elements of gendered digital media as a central feature of this ecosystem and a priority for subsequent research.

7 Conclusion

This paper provides the first episode-level map of the top U.S. podcast ecosystem focused on its role in a presidential election to interrogate media narratives that Trump's use of podcasts were decisive to the widening gender gap. In doing so, we introduce a new concept, gendered media spaces, to provide clarity on how candidates might choose entertainment podcasts to find persuadable audiences in a highly polarized environment. Specifically we articulate how gender intersects with the podcast ecosystem and provide evidence that gendered media spaces are connected to increases in political content, in particular conservative content, in ostensibly non-political podcasts. We find that masculine and conservative content co-occur systematically across this digital media ecosystem. Candidates, Trump in 2024 especially, seemingly honed in on gendered spaces in their appearance decisions, tracking a podcast's gender expression more closely than its ideology. The Harris campaign instead tracked ideology, concentrating its appearances among audiences already in her coalition, a pattern more consistent with mobilizing existing supporters than persuading new ones.

Young men were differentially exposed to conservative content through their entertainment podcast consumption. This differential exposure is associated with higher Trump vote intention in individual-level models after accounting for partisanship, and with 2024 Trump

vote choice after additionally accounting for prior vote history. The vote intention association is largest among Independents, precisely the voters campaigns most hope to persuade, consistent with our account of gendered media spaces as venues for reaching listeners who are not already sorted into partisan media. These associations are meaningful but modest in size, and by themselves do not plausibly explain the full 2024 widening of the youth gender gap. Taken together, these findings are consistent with popular accounts of Trump's podcast strategy, though *not* with some popular accounts of the impact of that strategy, and provide a theoretical account of the mechanism through which that strategy may have operated.

An important takeaway from this study is that the seemingly non-political media spaces can be influential in elections. To fully capture the information environment that voters inhabit, scholars must attend to ostensibly non-political spaces and the non-ideological dimensions along which audiences in those spaces are sorted. Gendered expression, specifically the degree to which a media space is masculine or feminine in its topics and speech patterns, emerges as a politically relevant signal that can guide candidate outreach toward audiences not otherwise reachable through ideologically sorted outlets. This has implications for how scholars model the information environment and for how we understand strategic campaign communication in an era when entertainment and political media are increasingly intertwined. This line of work has broad implications for research on political communication and political behavior by establishing the podcast medium as a consequential space for candidates seeking to reach audiences that may shape electoral outcomes.

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A Individual Level Models

A.1 Edison Podcast Metrics: Individual-Level Listener Data

Table A1: Conservative podcast exposure and Trump vote intent (log odds) by party

	By party
Con. listening index (Dem. reference)	0.003 (0.002)
× Independent	0.007** (0.002)
× Republican	0.003 (0.003)
Independent	2.622*** (0.125)
Republican	5.307*** (0.163)
Man (vs woman)	-0.029 (0.152)
Young, 34 or under (vs older)	0.067 (0.166)
Man × Young	0.209 (0.220)
Black (vs white)	-0.266 (0.164)
Hispanic (vs white)	0.195 (0.150)
Other race (vs white)	-0.138 (0.255)
College graduate	-0.544*** (0.126)
Income quartile 2	0.180 (0.155)
Income quartile 3	-0.063 (0.156)
Income quartile 4	-0.515** (0.172)
Weekly listening hours (logged)	0.167* (0.078)
Survey wave 2	-0.207 (0.143)
Survey wave 3	0.107 (0.143)
Survey wave 4	-0.377* (0.190)
N	3,544
Majority-class baseline	50.3
Correctly classified	86.9
Increase (pp)	36.7
Tjur D (overall)	0.613
Tjur D (conservative index)	0.014
* p < 0.05, ** p < 0.01, *** p < 0.001	

Log-odds coefficients with standard errors in parentheses; survey-weighted. Reference categories: Democrat, older women, white, income quartile 1, survey wave 1.

Table A2: Conservative podcast exposure and Trump vote intent (log odds) by sex-age-group

	By sex-age group
Con. listening index (young men ref.)	0.005** (0.002)
× Older men	0.002 (0.002)
× Young women	-0.000 (0.003)
× Older women	0.003 (0.003)
Older men	-0.301 (0.155)
Young women	-0.236 (0.172)
Older women	-0.263 (0.172)
Independent	2.623*** (0.127)
Republican	5.306*** (0.167)
Black (vs white)	-0.275 (0.166)
Hispanic (vs white)	0.184 (0.153)
Other race (vs white)	-0.137 (0.259)
College graduate	-0.533*** (0.128)
Income quartile 2	0.183 (0.158)
Income quartile 3	-0.062 (0.159)
Income quartile 4	-0.507** (0.176)
Weekly listening hours (logged)	0.130 (0.078)
Survey wave 2	-0.218 (0.146)
Survey wave 3	0.078 (0.146)
Survey wave 4	-0.385* (0.194)
N	3,544
Majority-class baseline	50.3
Correctly classified	86.9
Increase (pp)	36.7
Tjur D (overall)	0.610
Tjur D (conservative index)	0.011

* p < 0.05, ** p < 0.01, *** p < 0.001

Log-odds coefficients with standard errors in parentheses; survey-weighted. Reference categories: Democrat, young men, white, income quartile 1, survey wave 1.

A.2 YouGov Panel: Nationally Representative Individual-Level Data

Table A3: YouGov Rogan Listenership and 2024 Trump Vote

	No prior vote	+ 2020 vote	+ 2016 vote	+ Trump Both '16/'20
Rogan Listener	2.029*** (0.311)	1.743** (0.565)	2.544*** (0.464)	2.284*** (0.542)
Trump 2016 and 2020 vote				5.770*** (0.529)
2020 Trump vote		5.268*** (0.494)		
2016 Trump vote			4.845*** (0.392)	
Age	0.019** (0.007)	0.001 (0.013)	-0.012 (0.011)	-0.026 (0.015)
Woman	-0.336 (0.213)	-0.451 (0.398)	-0.482 (0.307)	-0.531 (0.405)
Black	-0.774* (0.355)	1.471* (0.609)	0.778 (0.524)	0.842 (0.598)
Hispanic	-0.108 (0.364)	-0.556 (0.715)	0.507 (0.612)	0.670 (0.775)
Income quintile	-0.075 (0.085)	-0.140 (0.159)	-0.071 (0.123)	-0.189 (0.165)
BA or higher	-0.686** (0.233)	-0.159 (0.442)	-0.652 (0.346)	-0.278 (0.462)
Republican	6.498*** (0.378)	4.030*** (0.611)	4.460*** (0.466)	4.022*** (0.594)
Independent	3.608*** (0.317)	2.611*** (0.546)	2.210*** (0.412)	1.728** (0.532)
N	1167	1167	931	931
Majority-class baseline	53.5	53.5	52.8	52.8
Correctly classified	89.3	96.5	95.1	96.7
Increase (pp)	35.8	43.0	42.2	43.8
Tjur D (Rogan)	0.030	0.002	0.007	0.006

Log-odds coefficients, standard errors in parentheses. Outcome is Trump 2024 vote. Tjur D is incremental over no-Rogan model. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table A4: Trump Appearance Channels and Trump 2024 Vote — Individual Models

	Rogan	Full Send	Theo Von	Flagrant
Rogan Listener	1.743** (0.565)			
Full Send Listener		−0.422 (1.428)		
Theo Von Listener			0.449 (1.026)	
Flagrant Listener				3.523** (1.080)
2020 Trump vote	5.268*** (0.494)	5.425*** (0.521)	5.435*** (0.503)	5.529*** (0.542)
Age	0.001 (0.013)	−0.009 (0.013)	−0.008 (0.013)	−0.004 (0.013)
Woman	−0.451 (0.398)	−0.509 (0.414)	−0.486 (0.398)	−0.458 (0.425)
Black	1.471* (0.609)	1.573* (0.633)	1.541* (0.607)	1.540* (0.643)
Hispanic	−0.556 (0.715)	−0.231 (0.760)	−0.242 (0.733)	−0.108 (0.803)
Income quintile	−0.140 (0.159)	−0.103 (0.163)	−0.109 (0.157)	−0.110 (0.167)
BA or higher	−0.159 (0.442)	−0.036 (0.462)	−0.008 (0.444)	−0.002 (0.472)
Republican	4.030*** (0.611)	3.760*** (0.613)	3.695*** (0.587)	4.039*** (0.642)
Independent	2.611*** (0.546)	2.397*** (0.548)	2.378*** (0.529)	2.681*** (0.584)
N	1167	1167	1167	1167
Listeners (N)	201	22	41	19
Majority-class baseline	53.5	53.5	53.5	53.5
Correctly classified	96.5	96.9	96.8	96.7
Increase (pp)	43.0	43.4	43.4	43.2
Tjur D (podcast)	0.002	0.000	0.000	0.003

Log-odds coefficients, standard errors in parentheses. Outcome = Trump 2024 vote. Each column is a separate model for one channel with 2020 Trump vote and demographic controls. Tjur D is incremental over no-podcast model. Listeners (N) is the number of respondents in the analytic sample who selected that channel. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table A5: YouGov Podcast Listenership and 2024 Trump Vote — Bayesian Multilevel Model by Sex-Age Group

	(1) Rogan	(2) Trump-any	(3) Harris-any
Fixed Effects			
Rogan Listener	1.70 [0.47, 2.81]		
Any Trump-appearance podcast		1.43 [0.15, 2.57]	
Any Harris-appearance podcast			0.24 [-1.95, 2.27]
2020 Trump vote	5.38 [4.59, 6.21]	5.48 [4.66, 6.35]	5.70 [4.88, 6.57]
Black	1.47 [0.47, 2.47]	1.46 [0.44, 2.50]	1.42 [0.44, 2.42]
Hispanic	-0.54 [-1.68, 0.66]	-0.53 [-1.67, 0.72]	-0.20 [-1.30, 0.93]
Income quintile	-0.12 [-0.39, 0.13]	-0.12 [-0.37, 0.15]	-0.05 [-0.31, 0.21]
BA or higher	-0.08 [-0.78, 0.65]	-0.03 [-0.76, 0.71]	0.08 [-0.64, 0.82]
Independent	2.44 [1.60, 3.33]	2.38 [1.52, 3.26]	2.37 [1.51, 3.26]
Republican	3.89 [2.94, 4.90]	3.72 [2.74, 4.70]	3.59 [2.66, 4.55]
Random Effects: sex-age group			
SD (Intercept)	0.55 [0.03, 1.68]	0.53 [0.02, 1.65]	0.29 [0.01, 1.12]
SD (Treatment slope)	0.56 [0.02, 1.89]	0.67 [0.03, 2.08]	1.98 [0.70, 4.00]
Corr (Intercept, slope)	0.08 [-0.92, 0.95]	0.11 [-0.91, 0.96]	0.14 [-0.89, 0.96]
First difference by group (pp)			
Young men	+7.0 pp [1.9, 12.5]	+5.4 pp [-0.0, 10.6]	+1.1 pp [-6.8, 8.3]
Older men	+7.7 pp [3.6, 14.0]	+7.3 pp [3.2, 13.7]	+11.3 pp [3.7, 21.1]
Older women	+5.4 pp [1.2, 11.0]	+4.3 pp [0.4, 9.0]	-0.9 pp [-11.0, 4.1]
Young women	+7.4 pp [-0.3, 14.1]	+6.0 pp [-1.6, 12.6]	-7.4 pp [-28.0, 2.6]
N	1,167	1,167	1,167
N groups (sex-age)	4	4	4
First difference (pp)	+6.7 pp [3.2, 11.1]	+5.8 pp [2.6, 9.7]	+3.7 pp [-1.7, 8.6]

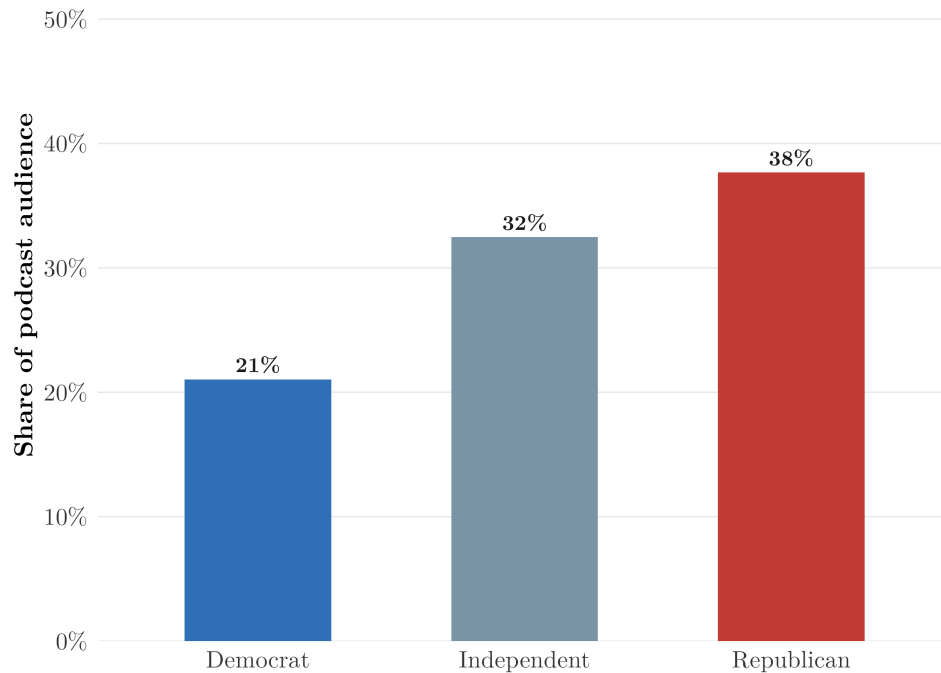
Log-odds coefficients, 95% credible intervals in brackets. Bayesian multilevel model: random intercept + random slope on the treatment by sex-age group. First difference by group is the average change in predicted Pr(Trump vote) for a listener versus an otherwise-identical non-listener within each sex-age group, holding controls fixed; the pooled first difference (bottom row) is the same quantity averaged over the full sample.

B Partisan Composition of Trump Non-Political Interview Audiences

Figure A1 shows the party identification composition of the ten non-political genre podcast audiences on which Trump appeared in 2024. Each bar represents the unweighted mean share of Democrats, Independents, and Republicans across the ten podcasts, drawn from EPM audience data. We cannot provide raw party identification for each channel as it is proprietary data, but we see across the sample 53% of the audience is not already sorted to Republican identification, meaning that there is tangible cross-party and independent

contact when Trump ventures onto these shows. The bar for those who selected none of the above is omitted.

Figure A1: PID of Audiences for Non-Political Podcasts Visited by Trump



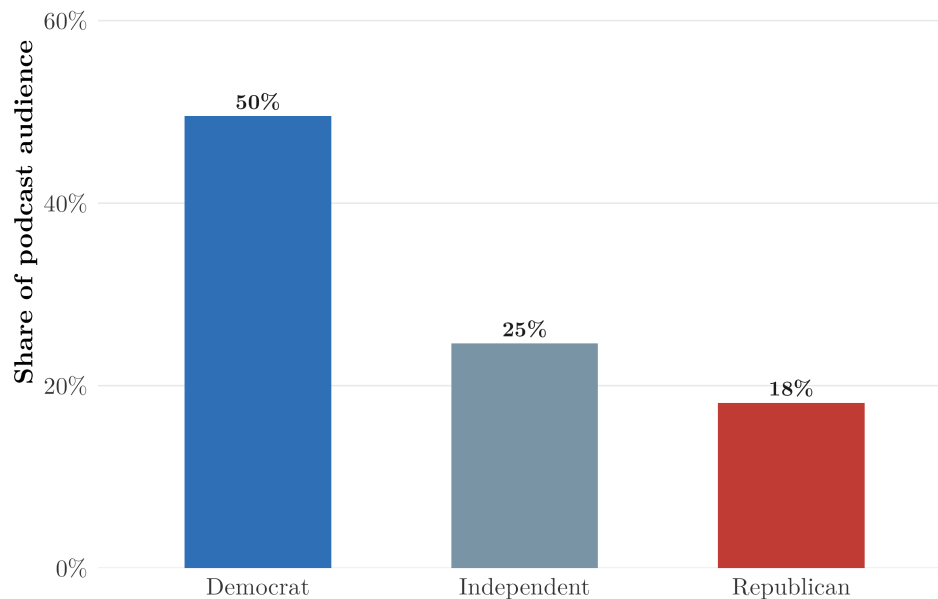
Note: The figure shows the distribution of party identification among audiences for the ten podcasts classified in nonpolitical genres that hosted Donald Trump in 2024. Audience estimates come from Edison Podcast Metrics. Respondents who selected “none of the above” are omitted from the figure.

C Partisan Composition of Harris Non-Political Interview Audiences

Figure A2 shows the party identification composition of the five non-political genre podcast audiences on which Harris appeared in 2024. Each bar represents the unweighted mean share of Democrats, Independents, and Republicans across the five podcasts, drawn from EPM audience data omitting from the figure the individuals who said none of the above. We cannot provide raw party identification for each channel as it is proprietary data, but we

see across the sample the largest share of the audience are already overtly Democrats (50% vs 43% combining Republicans and Independents). We interpret this as Harris attempting to target mostly Democrats (mobilization) as compared to Trump where the majority was in the out-party or independent category (persuasion).

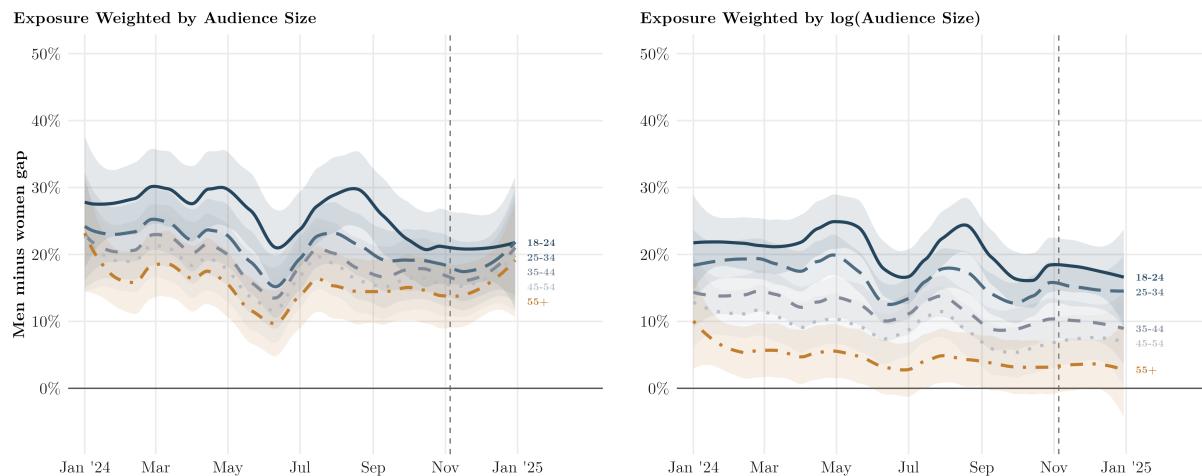
Figure A2: PID of Audiences for Non-Political Podcasts Visited by Harris



Note: The figure shows the distribution of party identification among audiences for the five podcasts classified in nonpolitical genres that hosted Kamala Harris in 2024. Audience estimates come from Edison Podcast Metrics. Respondents who selected “none of the above” are omitted from the figure.

D Conservative Exposure Gap Five Age Groups

Figure A3: Gender Gaps in Conservative Podcast Exposure Across Five Age Groups



Note: The figure shows men’s conservative podcast exposure minus women’s exposure within five age groups from January 2024 to January 2025. The sample includes only podcasts classified in non-political genres. The left panel weights podcasts by raw audience size, while the right panel weights podcasts by the logarithm of audience size. In both specifications, the two youngest age groups, ages 18–24 and 25–34, cluster above the three older age groups, ages 35–44, 45–54, and 55+.

E Conservative Exposure Gap: Podcast-Level Drivers

Table A6 identifies the ten non-political genre podcasts that contribute most to the conservative podcast exposure gap between men and women, shown separately for under-35 and 35+ age groups and for both the raw and log(audience size) weighting specifications used in Figure 6. This allows direct comparison of which podcasts drive the gap under each weighting approach.

Calculation. For each podcast c and week t , computed separately within each age group a , the podcast’s contribution to that week’s gap is

$$\hat{c}_{ct} = p_{ct} \cdot (s_{ct}^M - s_{ct}^W)$$

where p_{ct} is the podcast's share of conservative directional episodes in week t , and s_{ct}^M, s_{ct}^W are its shares of the total male and female demographic weight among all podcasts in age group a that week. The table reports results under two weighting schemes matching Figure 6: raw audience size, where each listener counts equally, and $\log(\text{audience size})$, which reduces the dominance of the largest podcast (Rogan). The reported figure averages $\hat{c}_{ct}$ across all weeks in which the podcast appears.

Interpretation. A podcast contributes positively when it combines conservative content with a male-skewed audience relative to the field in a given week. Values are expressed in percentage points of the weekly gap. Under $\log(\text{audience size})$ weighting, the Full Send Podcast is the largest contributor to the under-35 gap, with 95% of its political episodes leaning conservative and a 91% male under-35 audience share, contributing an average of +3.403 percentage points per week. Under raw audience weighting, *The Joe Rogan Experience* dominates given its large absolute audience, contributing +19.5 percentage points to the under-35 gap per week.

Table A6: Top 10 Channels Driving the Conservative Exposure Gender Gap

Rank	Channel	% Cons.	Male Share	Avg. Weekly Contribution
<i>Under 35 — Exposure Weighted by Audience Size</i>				
1	The Joe Rogan Experience	86.5%	78.3%	+19.484 pp
2	Impulsive with Logan Paul	87.5%	83.3%	+1.848 pp
3	This Past Weekend w/ Theo Von	65.9%	73.7%	+1.729 pp
4	Bad Friends	66.7%	76.6%	+1.321 pp
5	FULL SEND PODCAST	95.2%	91.9%	+1.246 pp
6	Matt and Shane's Secret Podcast	85.1%	85.5%	+1.114 pp
7	The Pat McAfee Show	77.8%	88.4%	+1.065 pp
8	2 Bears, 1 Cave with Tom Segura & Bert Kreischer	51.6%	78.6%	+0.887 pp
9	Pardon My Take	57.1%	87.4%	+0.831 pp
10	KILL TONY	91.1%	75.8%	+0.830 pp
<i>35 and Over — Exposure Weighted by Audience Size</i>				
1	The Joe Rogan Experience	86.5%	78.3%	+18.655 pp
2	The Pat McAfee Show	77.8%	88.4%	+1.263 pp
3	This Past Weekend w/ Theo Von	65.9%	73.7%	+0.846 pp
4	Bad Friends	66.7%	76.6%	+0.598 pp
5	Shawn Ryan Show	92.0%	76.9%	+0.525 pp
6	Club Shay Shay	24.0%	78.1%	+0.513 pp
7	2 Bears, 1 Cave with Tom Segura & Bert Kreischer	51.6%	78.6%	+0.484 pp
8	Pardon My Take	57.1%	87.4%	+0.467 pp
9	Lex Fridman Podcast	57.4%	84.7%	+0.449 pp
10	The Jordan B. Peterson Podcast	95.2%	74.5%	+0.449 pp
<i>Under 35 — Exposure Weighted by log(Audience Size)</i>				
1	FULL SEND PODCAST	95.2%	91.9%	+3.403 pp
2	Impulsive with Logan Paul	87.5%	83.3%	+2.493 pp
3	The Church of What's Happening Now: The New Testament	100.0%	90.7%	+2.435 pp
4	Matt and Shane's Secret Podcast	85.1%	85.5%	+2.369 pp
5	Club 520 Podcast	61.5%	95.1%	+2.280 pp
6	The Tim Dillon Show	95.7%	87.2%	+2.181 pp
7	Andrew Schulz's Flagrant with Akaash Singh	83.3%	83.2%	+1.925 pp
8	KILL TONY	91.1%	75.8%	+1.532 pp
9	The Joe Rogan Experience	86.5%	78.3%	+1.510 pp
10	Bussin' With The Boys	70.0%	95.2%	+1.492 pp
<i>35 and Over — Exposure Weighted by log(Audience Size)</i>				
1	The Pat McAfee Show	77.8%	88.4%	+1.383 pp
2	The Joe Rogan Experience	86.5%	78.3%	+1.299 pp
3	Jocko Podcast	94.3%	82.7%	+1.299 pp
4	The Dan Patrick Show	48.2%	90.7%	+1.225 pp
5	All-In with Chamath, Jason, Sacks & Friedberg	100.0%	78.1%	+1.169 pp
6	Valuetainment Podcast	81.8%	75.8%	+1.156 pp
7	Shawn Ryan Show	92.0%	76.9%	+1.147 pp
8	The Jordan B. Peterson Podcast	95.2%	74.5%	+1.106 pp
9	The Tim Dillon Show	95.7%	87.2%	+0.960 pp
10	The Meateater Podcast	71.4%	81.8%	+0.929 pp

Non-political genre channels only. Each channel's average weekly contribution is computed as $\hat{c}_{ct} = p_{ct} \cdot (s_{ct}^M - s_{ct}^W)$, where p_{ct} is the channel's share of conservative directional episodes in week t , and s_{ct}^M, s_{ct}^W are its shares of the total male and female audience weights in week t . Audience size weights are raw listener counts; log(audience size) weights dampen the influence of the largest shows. Contributions are in percentage points.

F Vote Gap

Table A7: **Gender Gap by Age — Women’s Democratic Support Minus Men’s Support**

Table Generated from Catalist Report

Age Group	2012	2016	2020	2024
18–29	+8.5	+13.5	+10.5	+16.0
30–44	+9.0	+13.0	+9.0	+13.0
45–65	+8.5	+12.0	+9.0	+12.0
65+	+7.0	+10.5	+8.5	+11.5

Table A8: **Gender Gap by Age — Republican Support Men’s Minus Women’s Support**

Original Analysis of AP VoteCast

Age Group	2020	2024
18–24	+10	+16
25–29	+4	+11
30–39	+4	+7
40–49	+9	+6
50–64	+8	+6
65+	+10	+9

G Validation

We evaluate classifier performance against four research assistants (RAs) who annotated 992 speaker utterances drawn from a stratified sample of 1,000 annotated tasks, with 500 selected at random across the full podcast corpus and 500 oversampled from chunks the LLM flagged as containing political content. Of the 1,000 tasks, 992 achieved full four-RA coverage and form the analytic sample below. RAs annotated all tasks independently using Label Studio and were blind to LLM labels throughout. For each task we also report Krippendorff’s α among RAs as an estimate of the human agreement ceiling, the upper bound on agreement any classifier can be expected to reach given ambiguity in the task. All weighted κ values use squared weights; α is computed under the nominal metric for binary and directional tasks.

Detection

The politics detection task has an explicit Yes/No structure in both the LLM and RA annotation stages. Against the modal RA label per task, the classifier achieves 84.7% overall accuracy and 90.9% accuracy on the 689 tasks where all four RAs unanimously agreed on the detection label ($\kappa = 0.700$; RA–RA ceiling $\alpha = 0.657$). The gap between overall and unanimous-item accuracy reflects contested tasks where human annotators disagree, not classifier error; on the unambiguous items the classifier approaches the human ceiling. (Modal RA label tie-breaking was previously silently alphabetical, e.g. always resolving a 2–2 split toward “No”; fixed to only resolve non-substantive ties, with cross-category ties excluded rather than arbitrarily broken. 85 of 992 politics tasks were ties.)

Gender behavior and gender topics detection require a different interpretive frame because of the labeling interface used. The LLM uses an explicit two-stage gate. It decides first whether gendered content is present, then scores lean only if Yes. RAs, by contrast, annotated a unified 7-point ordinal scale with no separate detection step; we derive their detection label from lean (neutral is No; any directional label is Yes). When one RA writes “neutral” and another writes “slightly masculine,” labels one step apart on the 7-point scale, this registers as a full detection disagreement even though their underlying assessments are nearly identical. Among tasks where RAs disagreed on derived detection, 91% of gender behavior disagreements and 65% of gender topics disagreements are these distance-1 boundary cases. The lean ordinal statistics reported below provide the appropriate reliability benchmark for these dimensions. Unambiguous-item accuracy (all four RAs unanimous) reaches 94.7% for gender behavior (508 unanimous tasks) and 74.1% for gender topics (243 unanimous tasks).

Table A9: LLM vs. human consensus.

Dimension	Stage	n	Acc. (unan.)	Acc. (overall)	κ	α (ceiling)
<i>Detection</i>						
Politics	Detection	907	0.909	0.847	0.700	0.657
Gender behavior	Detection*	867	0.947	0.896	0.449	—
Gender topics	Detection*	711	0.741	0.655	0.261	—
<i>Directional lean</i>						
Gender behavior	Directional lean	622	0.908	0.870	0.598	0.305
Gender topics	Directional lean	255	0.895	0.922	0.735	0.555
Ideology	Directional lean	210	0.978	0.929	0.834	0.556

Modal RA label per task used as reference. *Acc. (unan.)* is accuracy on tasks where all four RAs unanimously agreed (detection rows) or where all non-neutral RAs agreed on direction (lean rows). *Acc. (overall)* covers all tasks. κ = unweighted Cohen's κ . α = Krippendorff's α (nominal) among RAs.

* Gender detection derived from lean (neutral is No; directional is Yes). RA–RA α suppressed; conflates detection disagreement with scale-boundary cases (see prose above table).

Full Ordinal Scale Agreement

Table A10 reports agreement on the full 7-point ordinal scale using squared-weighted κ (κ_w) between the LLM and modal RA consensus, alongside mean pairwise RA–RA κ_w as the human-agreement ceiling. The LLM–RA κ_w exceeds the RA–RA ceiling for all three dimensions, indicating the classifier agrees with the modal RA as reliably as or more reliably than individual RAs do relative to that consensus. Ideology lean shows the strongest ordinal agreement ($\kappa_w = 0.724$) against a ceiling of 0.549. Gender behavior ($\kappa_w = 0.573$; ceiling 0.336) and gender topics ($\kappa_w = 0.557$; ceiling 0.342) are lower in absolute terms but exceed the human ceiling by 71% and 63%, respectively, confirming these reflect task ambiguity rather than classifier underperformance. Within-1 accuracy (the share of predictions within one scale step of the modal RA label) is 81.4%, 72.5%, and 82.1% for gender behavior, gender topics, and ideology, indicating that errors are predominantly near-neighbor intensity misplacement rather than directional reversals. We report full ordinal scale agreement for clarity; however, we use directional lean for all main analyses.

Table A10: Lean ordinal agreement.

Dimension	n	κ_w (LLM–RA)	κ_w (RA–RA)	Within-1	MAE
Gender behavior	828	0.573	0.336	0.814	0.958
Gender topics	739	0.557	0.342	0.725	0.857
Ideology	430	0.724	0.549	0.821	0.740

κ_w = weighted Cohen’s κ (squared weights). LLM–RA compares LLM to modal RA consensus. RA–RA is mean pairwise κ_w among the four RAs (human-agreement ceiling). Within-1 is the share of predictions within one scale step of modal RA. MAE is the mean absolute error in scale steps.

Directional Accuracy

Because the paper’s primary claims concern the direction of content, whether podcasts carry conservative or liberal content, masculine or feminine content, we separately assess directional accuracy: whether the classifier correctly identifies the direction of lean, ignoring intensity. For ideology we collapse the 7-point scale to liberal (positions 1–3) vs. conservative (positions 5–7), excluding neutral/moderate chunks (position 4). For gender we collapse to feminine (positions 1–3) vs. masculine (positions 4–6).

Directional accuracy is high for all dimensions. Ideology direction is correct in 92.9% of cases ($\kappa = 0.834$; RA–RA ceiling $\alpha = 0.556$), indicating the classifier exceeds the human ceiling. Gender topics direction is correct in 92.2% of cases ($\kappa = 0.735$; RA–RA $\alpha = 0.555$). Gender behavior direction is correct in 87.0% of cases ($\kappa = 0.598$), with a modest asymmetry where the classifier identifies masculine-coded speech more reliably ($F1 = 0.918$) than feminine-coded speech ($F1 = 0.680$). This asymmetry mirrors RA–RA pairwise agreement where human annotators also agree less on feminine labels, reflecting that feminine directional content is rarer and more contextually ambiguous in the corpus rather than a systematic classifier bias. The RA–RA directional α is 0.305 for gender behavior, 0.555 for gender topics, and 0.556 for ideology, confirming the classifier meets or exceeds the human ceiling on all three dimensions. The low α for gender behavior direction warrants additional comment. A previous validation run on the same annotation instrument with a different cohort of six RAs yielded an RA–RA α of 0.415 for the same binary masculine/feminine judgment.

The variation across cohorts indicates that the difficulty is annotator-specific rather than an inherent ceiling on the construct: a more experienced or better-calibrated annotator pool recovers higher inter-rater agreement on the same labels. The classifier’s κ of 0.598 exceeds the current cohort’s ceiling ($\alpha = 0.305$) by 96% and the prior cohort’s ceiling ($\alpha = 0.415$) by 44%, suggesting it has learned a stable directional signal that individual annotators access inconsistently depending on their calibration.

Table A11: Directional accuracy, LLM vs. RAs.

Dimension	n	Acc. (overall)	κ (LLM–RA)	α (RA–RA)
Ideology	210	0.929	0.834	0.556
Gender topics	255	0.922	0.735	0.555
Gender behavior	622	0.870	0.598	0.305

Smaller sample size reflects gating. κ = unweighted Cohen’s κ (binary direction). α = Krippendorff’s α (nominal) among RAs. Ideology excludes neutral/moderate labels.

Detection Precision and Recall

Table A12 reports precision, recall, and F_1 for detection, using the modal RA label as the reference standard (positive = detected). Politics and gender behavior show near-perfect recall (0.987 and 0.993), indicating the classifier rarely misses content that RAs flag. Lower politics precision (0.738) reflects the political oversample design. Because half the validation sample was drawn from LLM-flagged political chunks, the LLM positive rate is elevated relative to RAs in that stratum. Lower gender behavior precision (0.896) is consistent with the boundary analysis. The LLM applies a slightly lower detection threshold than RAs, but 91% of the resulting disagreements are distance-1 cases where RA labels cluster at the neutral–slightly boundary. Gender topics shows higher precision (0.840) than recall (0.655).

Table A12: Detection precision, recall, and F_1 .

Dimension	n	Precision	Recall	F_1
Politics	907	0.738	0.987	0.845
Gender behavior	867	0.896	0.993	0.942
Gender topics	711	0.840	0.655	0.736

RA modal label as reference; positive = detected. Precision = share of LLM-positive items confirmed by RA consensus; Recall = share of RA-positive items also flagged by LLM.

H Convergent Validity

Beyond agreement with human annotators, we assess the convergent validity of our classifier scores across two complementary tests: (1) cross-run replication against an independent scoring run using a different model and slightly different prompts, and (2) correlation with ideological benchmarks constructed from TikTok follower networks by Piqueras et al. (2025) using an entirely independent data source and methodology. Together these tests ask whether our classifier recovers a stable underlying signal.

H.1 Comparing Runs of Gemini 3 Flash vs. Gemini 2.5 Flash Lite

Our primary scores are produced by Google Gemini 3 Flash via the Vertex AI batch API through Portkey. As an independent replication check, we compare these scores to an earlier scoring run on the same corpus using Gemini 2.5 Flash Lite not through batch processing, but independent requests on Portkey, which used a less verbose prompt structure (fewer political definitions, less expansive definition of politics), and with a different and smaller model. We aggregate both runs to the podcast level (episode mean, weighted by chunk count) and compute Pearson and Spearman correlations across the 214 podcasts present in both runs.

Table A13 reports correlations for ideology and gender. Both dimensions show strong cross-run agreement despite the model-version difference, with ideology ($r = 0.833$, $\rho =$

0.762) replicating more tightly than gender expression ($r = 0.771$, $\rho = 0.802$). The lower gender correlation partly reflects the structural improvement in the Gemini 3 run where the newer model is better calibrated on the “slightly” intensity level (as noted in Appendix Validation Section G), shifting some podcast scores modestly toward the midpoint. Directional agreement remains high, podcasts coded as masculine-leaning by Gemini 2.5 are coded masculine-leaning by Gemini 3, and similarly for ideology direction.

Table A13: Cross-run correlation: Gemini 3 Flash (primary) vs. Gemini 2.5 Flash Lite (earlier run). Unit of observation is a podcast ($N = 214$ podcasts present in both runs; each row’s N may be smaller after requiring a finite score in both runs on that dimension). Scores are episode-level chunk-weighted means aggregated to podcast level.

Comparison	N	Pearson r	Spearman ρ
Ideology (political-only)	201	0.833	0.762
Gender expression (combined)	214	0.771	0.802

H.2 External Benchmark: TikTok Ideological Scores

We further validate our ideology scores against TikTok ideological scores constructed by Piqueras et al. (2025) from the partisan composition of TikTok followers of podcast hosts. These scores are available for the 57 podcasts in our sample whose hosts maintain a linked TikTok presence. The benchmark is constructed from an entirely independent data source (social media follower networks on a different platform) using a completely different methodology (follower partisanship rather than content classification), making it a strong test of convergent validity. Our political-only ideology score correlates with the TikTok-based score at $r = 0.782$ ($\rho = 0.742$, $N = 57$). We take this as further evidence that our LLM scoring is recovering meaningful political information from the digital ecosystem.

Table A14: Correlation between our ideology scores and TikTok-based ideological benchmark

	Pearson r	Spearman ρ
TikTok Ideology	0.782	0.742

I LLM Classification Prompts

Model and Infrastructure

All classification tasks were run using Google Gemini 3 Flash Preview, accessed via the Google Vertex AI batch inference API through use of Portkey.³⁸ Requests were submitted as asynchronous batch jobs with a 24-hour completion window. Each chunk receives a shared system prompt (below), followed by one of the six task-specific user prompts described in this appendix.

All prompts follow a two-stage design. A binary detection stage determines whether a given dimension is present in the chunk. If and only if the detector returns “Yes”, the chunk is passed to a direction-scoring stage. The choice of doing a detection and lean stage was based off of analysis done on previous scoring and human validation. The authors found that the LLM often overused neutral or moderate on both ideology and gender tasks, especially gender tasks. This was different than the RA labeler and the author (expert) labels which chose the moderate or neutral at a much lower rate. The gated approach of doing a detect then lean stage reduced the rate at which the model used a hedging category rather than making a call. The six detect and lean prompt tasks are:

1. Gender Behavior Detection (Stage 1)
2. Gender Behavior Direction (Stage 2)
3. Gender Topic Detection (Stage 1)
4. Gender Topic Direction (Stage 2)
5. Politics Detection (Stage 1)
6. Ideology Direction (Stage 2, politics gated)

³⁸<https://portkey.ai/>

Runtime placeholders {CONTEXT}, {TRANSCRIPT}, and {LABEL_TOPIC} are filled from the episode chunk record at inference time. {CONTEXT} is the preceding speaker turn for additional information when needed, {TRANSCRIPT} is the target segment to be labeled, and {LABEL_TOPIC} is a topic label drawn from chunk metadata and is used only in the gender topic prompts.

Shared System Prompt

Applied to every request across all six tasks.

```
You are a research assistant labeling a podcast transcript segment.  
Follow instructions carefully. Return only valid JSON. No extra text.
```

Task 1: Gender Behavior Detection (Stage 1)

Binary gate: does the chunk contain gender-coded *speech behavior*? Only chunks returning “Yes” proceed to Task 2.

Podcast Labelling Instructions

Task: Gendered Speech Behavior Detector (stage 1)

Goal: Detect whether the TARGET segment contains gender-coded speech behavior.

This is stage 1 only: do NOT assign masculine/feminine direction or intensity
↪ here.

Direction/intensity is handled in stage 2.

Use ONLY speech-style cues such as:

Feminine-coded: hedging ("I think," "maybe"), emotional or relational language,
affiliative or consensus-seeking, supportive tone, tag questions.

Masculine-coded: directive or competitive language, certainty/absolutes,

evaluative judgments, expertise signaling, confrontational or dominant tone.

Decision rules:

- Choose "Yes" if there is any meaningful gender-coded speech-style signal, even if subtle.
- Choose "No" only when cues are truly absent.
- Many real segments do contain gendered speech-style leanings; do not overuse "No" as a default.

Do NOT use:

- The gender of the speaker
- The topic alone
- Quoted or reported speech as evidence, unless the speaker adopts that style

Context (optional, only for understanding references):

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Choose exactly one: Yes, No

Return ONLY this JSON object with exactly one key:

```
{  
  "gender_behaviors": "Yes_or_No"  
}
```

Task 2: Gender Behavior Direction (Stage 2)

Direction scoring for chunks that passed Stage 1. Neutral is not permitted.

Podcast Labelling Instructions

Task: Gendered Behavior (ONLY) -- NON-NEUTRAL VERSION

This is a SECOND-STAGE prompt after a detector already found the segment to be gendered. Your job is to choose the **direction** of the gendered behavior.

Do NOT use neutral.

Rate how traditionally masculine or feminine the SPEECH STYLE / BEHAVIOR in the TARGET segment is. Focus on delivery, stance, and interactional style -- not

↪ the
topic.

Use ONLY speech-style cues such as:

Feminine-coded: hedging ("I think," "maybe"), emotional or relational language, affiliative or consensus-seeking, supportive tone, tag questions.

Masculine-coded: directive or competitive language, certainty/absolutes, evaluative judgments, expertise signaling, confrontational or dominant tone.

Strength guidance:

- slightly: a mild directional signal
- moderately: multiple cues in the same direction
- strongly: dominant, emphatic directional pattern

Do NOT use:

- The gender of the speaker

- The topic alone
- Quoted or reported speech as evidence, unless the speaker adopts that style

Context:

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Choose exactly one (neutral is NOT allowed):

strongly_masculine, moderately_masculine, slightly_masculine,
slightly_feminine, moderately_feminine, strongly_feminine

Return ONLY this JSON object with exactly one key:

```
{  
  "gender_behaviors": "one_choice_from_list"  
}
```

Rules:

- Return only JSON.
- The value must be exactly one of the allowed strings.

Task 3: Gender Topic Detection (Stage 1)

Binary gate: does the topic carry a culturally gendered association? Only chunks returning “Yes” proceed to Task 4.

Podcast Labelling Instructions

Task: Gendered Topic Detector (stage 1)

Goal: Detect whether the TARGET segment's topic has a clear gendered

↪ association.

This is stage 1 only: do NOT assign masculine/feminine direction or intensity

↪ here.

Direction/intensity is handled in stage 2.

Decision rules:

- Choose "Yes" if there is any meaningful gendered association in common

↪ cultural

framing, even if subtle.

- Choose "No" only when gendered association is truly absent.

Topic guidance (examples, not exhaustive):

- Often masculine-coded in common framing: sports, finance/investing, combat/military talk, performance cars/mechanics.

- Often feminine-coded in common framing: makeup/beauty, fashion styling, relationship advice, true crime storytelling.

- If a topic is discussed in a neutral, mixed, or broad way without clear gendered framing, choose "No".

Context (optional, only for disambiguation):

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Proposed Topic Label:

```
{LABEL_TOPIC}
```

Choose exactly one: Yes, No

Return ONLY this JSON object with exactly one key:

```
{  
  "gender_topics": "Yes_or_No"  
}
```

Rules:

- Return only JSON.
- The value must be exactly "Yes" or "No".

Task 4: Gender Topic Direction (Stage 2)

Direction scoring for chunks that passed Task 3. Neutral is not permitted.

Podcast Labelling Instructions

Task: Gendered Topic (ONLY) -- NON-NEUTRAL VERSION

This is a SECOND-STAGE prompt after a detector already found the segment to be gendered. Your job is to choose the **direction** of the gendered topic.

Do NOT use neutral.

Rate how traditionally masculine or feminine the TOPIC of the TARGET segment
↪ is.

Focus on broader cultural associations with the topic, not personal opinions.

Do NOT base your answer on ideology or politics.

Topic guidance (examples, not exhaustive):

- Often masculine-coded in common framing: sports, finance/investing, combat/military talk, performance cars/mechanics.
- Often feminine-coded in common framing: makeup/beauty, fashion styling, relationship advice, true crime storytelling.

Strength guidance:

- If signal is weak but directional, use "slightly_masculine" or "slightly_feminine".
- Use "moderately_masculine" or "moderately_feminine" when multiple cues point in the same direction.
- Only use "strongly_masculine" or "strongly_feminine" when cues are clearly consistent and strong.

Context:

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Proposed Topic Label:

{LABEL_TOPIC}

Choose exactly one (neutral is NOT allowed):

strongly_masculine, moderately_masculine, slightly_masculine,
slightly_feminine, moderately_feminine, strongly_feminine

Return ONLY this JSON object with exactly one key:

```
{  
  "gender_topics": "one_choice_from_list"  
}
```

Rules:

- Return only JSON.
- The value must be exactly one of the allowed strings.

Task 5: Politics Detection (Stage 1)

Binary gate for political content. Only chunks returning “Yes” proceed to Task 6.

Podcast Labelling Instructions

Task: Politics Detector (stage 1)

Decide whether the TARGET segment is about politics, political issues, or political figures. This Yes/No decision is the detector gate for ideology stage 2:

- "Yes" segments proceed to ideology direction/intensity scoring.
- "No" segments are not sent to ideology stage 2.

Segments about politics can include discussion about how we govern ourselves, distribute power, or resolve collective questions. This includes both formal political institutions and social controversies that have become matters of public debate.

A segment is political if it addresses things like:

- Government, legislation, public institutions, elections, or political

↪ figures.

- Public policies (e.g., taxes, healthcare, civil rights).
- Organized activities by the public to influence politics (e.g., protests, boycotts, writing letters to representatives, campaign donations).
- Geopolitical or international conflicts.
- Politically salient social and cultural issues debated in the public sphere, such as racism, sexism, LGBTQ rights, immigration, public health mandates, religion in public life, regulating education curricula, or free speech.

Context:

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Is this about politics? Choose exactly one: Yes, No

Return ONLY this JSON object with exactly this key:

```
{  
  "politics": "Yes_or_No"  
}
```

Rules:

Return only JSON.

politics must be exactly "Yes" or "No".

Task 6: Ideology Direction (Stage 2)

Applied only to segments classified as political in Stage 1. Unlike the gender direction prompts, “moderate” is permitted to accommodate neutral reporting and mixed-cue segments.

Podcast Labelling Instructions

Task: Ideology (stage 2, politics-gated)

This segment has already been labeled political by the Politics Yes/No
↔ detector.

This step is only run for segments where politics == "Yes".

Rate the ideological leaning expressed in the TARGET segment.

Use the speaker's stance, not the topic itself.

If the segment is purely descriptive, balanced, mixed between liberal and conservative cues, or reporting without endorsement (e.g., a straight news segment about politics), choose "moderate".

Lean cues (U.S. context):

- Liberal: support for redistribution, social safety nets, civil rights expansion, regulation, climate action, gun control, reproductive rights.
- Conservative: support for limited government, lower taxes, traditional social norms, deregulation, strong law-and-order, gun rights.

Intensity:

- slightly: mild or single cue
- moderately: multiple cues
- strongly: dominant, emphatic stance

- moderate: neither clearly liberal nor clearly conservative, including neutral political reporting or mixed cues without a directional stance

Context (optional, only for disambiguation):

{CONTEXT}

TARGET SEGMENT:

{TRANSCRIPT}

Choose exactly one:

strongly_conservative, moderately_conservative, slightly_conservative,
moderate,
slightly_liberal, moderately_liberal, strongly_liberal

Return ONLY this JSON object with exactly one key:

```
{  
  "ideology": "one_choice_from_list"  
}
```

Rules:

Return only JSON.

The value must be exactly one of the allowed strings.

J How to define politics and its subsequent implications

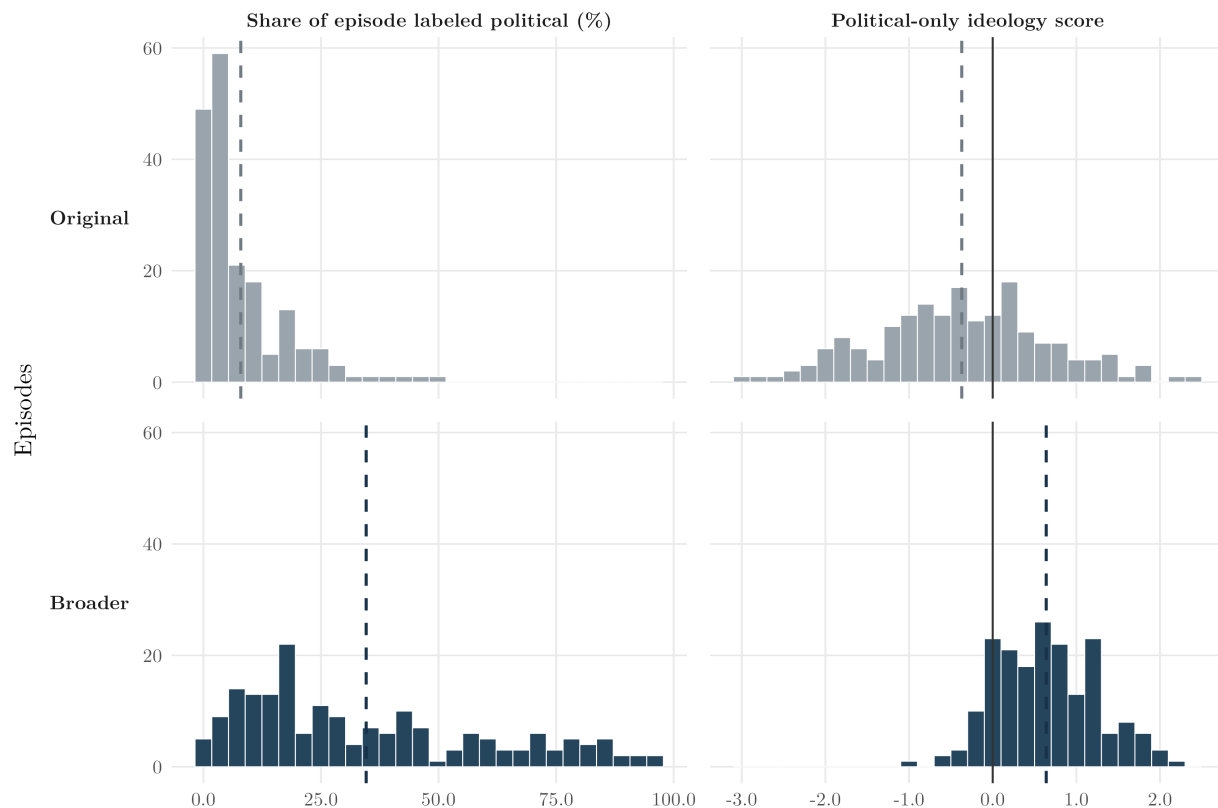
Ideological scores are influenced by how politics is defined in LLM prompting. We have undertaken two separate strategies on this front. Our initial politics identification (not featured in this paper) included a narrower definition of politics stating: “Please determine whether the TARGET SEGMENT is discussing politics. Politics is defined as related to elections, government, public policy, or political debates, including issues about how society is governed, who holds power, and the decisions that affect people’s lives.” Then if it was about politics, segments were considered to have a liberal lean if it included ideas about social equality, government intervention in the economy, and progressive social change. Conservative lean emphasized ideas such as individual responsibility, limited government, traditional social values, and national security. From there, the authors updated the politics classifier to a more verbose one listed in Section I. This was done after interrogating human labeled validation for the first prompt, and realizing the LLM was missing political discussion particularly around social issues. A good example of this discussion in the 2024 election cycle is trans rights. An LLM specifically prompted about elections and governance might miss how central trans women in women’s sports was to campaign commentary in 2024.

While our first definition of politics focused narrowly on elections and governance which was defensible and produced meaningful results, we believe the updated prompting more accurately reflects the scope of political discussion during the 2024 cycle. Below, we describe the substantive shifts that the revised prompting surfaced and show that the Trump interview podcasts featured a variety of ideological orientations.

Under the first definition of politics, a podcast like *The Joe Rogan Experience*, has a different measured distribution of ideology than in the second prompting strategy. In Figure A4 we show that the updated prompting strategy found more politics overall (the share of episode labeled as political increased, shown in the first panel), and that the overall

distribution of ideological lean shifted slightly conservative as opposed to the narrow politics measure that was slightly liberal (measured on the original full Likert scale where -3 is most liberal and 3 is most conservative).

Figure A4: Political Content and Ideological Scores Under Alternative Classification Strategies



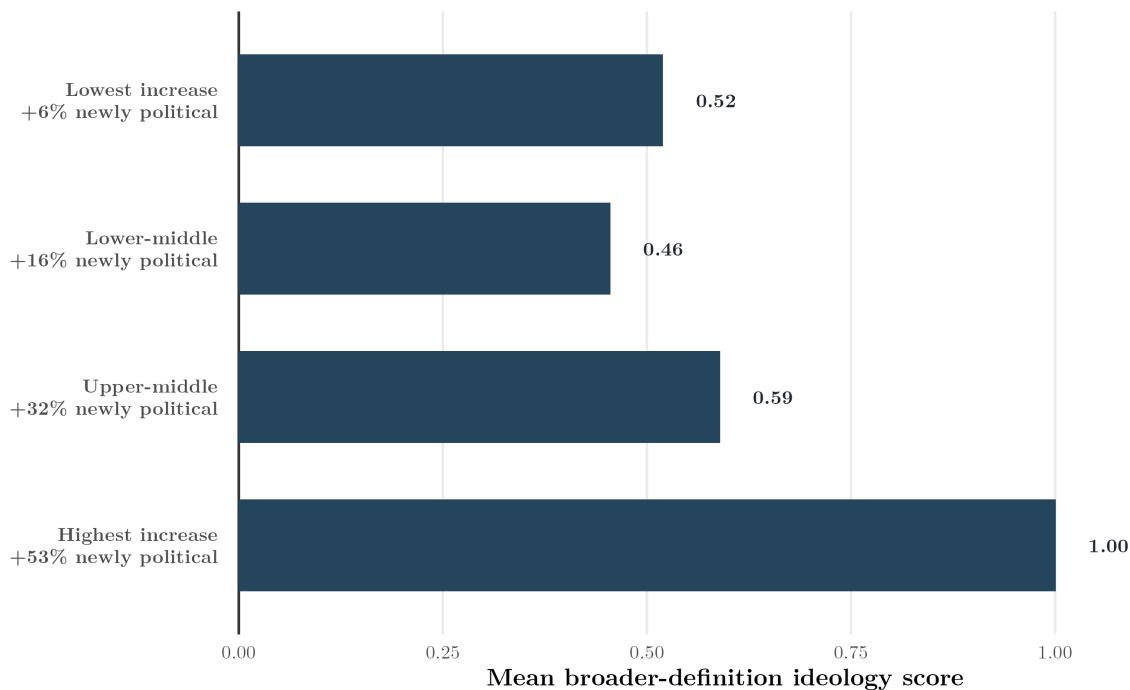
Note: The figure compares the distributions of political-content classifications and ideological scores produced under the original/old (narrow) politics definition and the new (broader) definition of politics.

This shift is consistent with the updated prompt capturing the social issue political content that the original prompt tended to miss. The newly classified political content is conservative-leaning indicating the model is picking up social issues that especially the comedy podcasts tend to weigh in on.

To confirm this, we group Rogan episodes by the increase in the share of the episode labeled political between the original and updated prompts. Figure A5 shows that episodes with the largest increase in politics labeling have the most conservative broader-definition ideology scores. This lines up with the updated social politics definition catching what

was previously omitted. We do see increases in conservative content in low politics change episodes, but the highest density comes from episodes where the most new political flags were added. This is also consistent with reducing the false negatives for politics through the detect/lean approach where the LLM was overusing neutral and moderate (referenced in Section I).

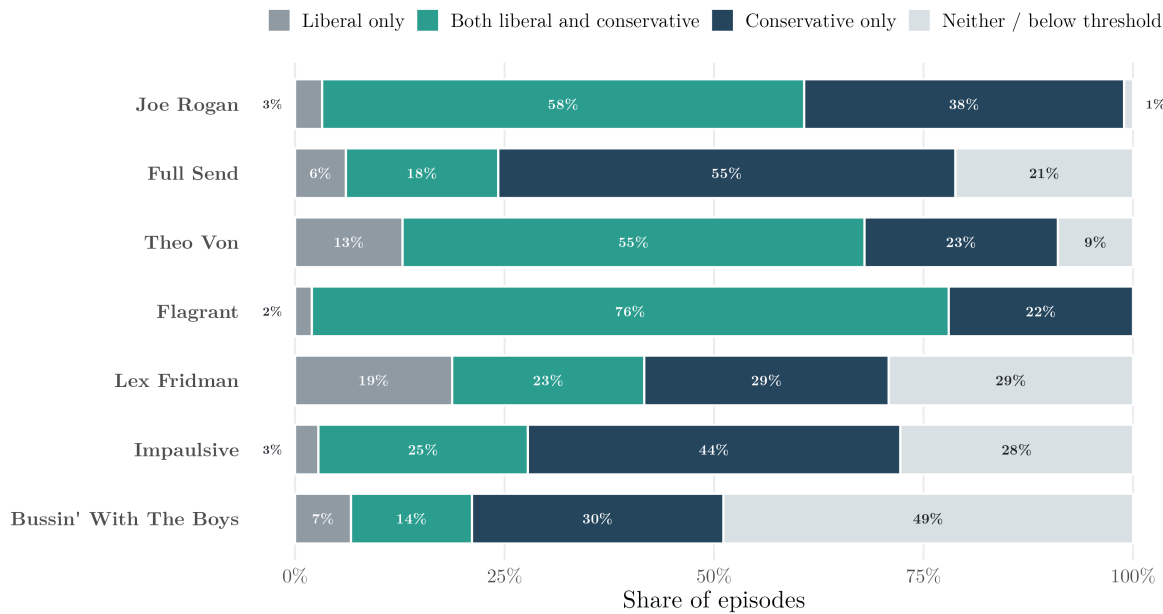
Figure A5: Changes in Political Content Identification and Conservative Ideology Scores



Note: Rogan episodes are grouped into quartiles based on the increase in the share of each episode classified as political under the updated prompt relative to the original prompt. The percentages shown in the group labels report the mean increase in political content within each quartile. Bars show the mean broader-definition ideology score, with higher values indicating more conservative content.

Finally, we see if there is a variety of political opinions featured in the podcasts, or if it under the new classification is uniformly conservative. Figure A6 classifies episodes from some Trump-interview podcasts into four mutually exclusive categories: liberal-only, conservative-only, both liberal and conservative, and neither/below threshold.

Figure A6: Ideological Distribution of Content on Podcasts Visited by Trump



Note: Episodes from the Trump-interview podcasts shown are classified into four mutually exclusive categories using the updated political-content definition. “Liberal only” and “conservative only” indicate that content associated with only that ideological direction exceeds the classification threshold. “Both” indicates that both liberal and conservative content exceed the threshold, while “neither/below threshold” indicates that neither does.

The figure shows that these podcasts frequently contain both liberal and conservative coded content and rarely feature only conservative takes. Rogan, Theo Von, and Flagrant in particular contain substantial evidence of a mix of conservative and liberal content. Thus, the revised prompt changes the net ideological balance of some podcasts, but it does not erase ideological heterogeneity across or within these podcasts.

K Transcription Pipeline Specifications and Validation

WhisperX Model Configuration

All 36,659 episodes were transcribed using WhisperX (Bain et al., 2023) with the `large-v3` model variant running at float16 precision on H200 (141GB HBM3) and L40S (48GB) GPUs. Transcription used “faster-whisper’s” batched inference pipeline starting at a batch size of 64,

with adaptive fallback to 32 and then 16 on out-of-memory errors. Voice activity detection (VAD) parameters were auto-tuned per episode using a histogram of silence gap durations, with the 25th percentile gap duration used as the silence splitting threshold (clamped between 150ms and 1500ms). Individual VAD segments were capped at 30 seconds to prevent GPU memory issues on long continuous speech. Following transcription, word-level forced alignment was performed via “whisperx.align” and speaker diarization was applied using PyAnnote’s “DiarizationPipeline”, which assigns speaker labels to each aligned word segment.

Transcription Quality Validation

Transcription quality was assessed through two independent manual review rounds, each covering a random sample of 50 episodes. The reviewer read the transcript text and listened to the corresponding audio, checking for accuracy in word recognition, speaker turn boundaries, and segment completeness.

A systematic hallucination pattern was identified during validation where a small subset of episodes exhibited repeated characters or repeated phrases at the end of the transcript file, concentrated in episodes processed at the end of large GPU batches. This artifact is a known failure mode of batched Whisper inference where the model enters a repetitive generation loop when audio ends mid-batch. Affected episodes were identified programmatically and retranscribed using smaller batch sizes (32 or 16), after which the hallucinated output was eliminated.

A separate validation pass was conducted at the LLM scoring stage. Scored speaker chunks were read alongside the original transcript text and, in a subset of cases, cross-referenced against the audio recording before sending off to the LLM for scoring to ensure the diarization, the chunking, and 750 character truncation were accurate to the audio.