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ECONOMIC JUSTICE

Data-Driven Audience Profiles for Narrative Change

Ariane Aumaitre Balado • Maheen Shermohammed
Maya Faulstich-Hon • Jeremy Barofsky • Eva Matos

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About ideas42

ideas42 is a nonprofit that applies insights from behavioral science—the study of how people make decisions and act in the real world—to improve lives and drive social change. Working globally, we reinvent the practices of institutions, and create more effective products and policies that can be scaled for maximum impact.

We also teach others, ultimately striving for a future where the universal application of behavioral science powers a world with optimal health, equitable wealth, and environments and systems that are sustainable and just for all.

For the past 15 years, we've been at the forefront of applying behavioral science to create a more equitable world. And as we've developed our expertise, we've helped to define an entire field. Our efforts have so far extended to 50+ countries as we've partnered with hundreds of governments, foundations, NGOs, private sector entities, and philanthropic leaders.

Visit ideas42.org and follow @ideas42 on Twitter to learn more about our work. Contact Eva Matos at ematos@ideas42.org for additional information.

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In the United States, there are deep-seated narratives about who deserves what, and why. One of the most pervasive and false sets of narratives in American society is that people experiencing poverty have only themselves to blame—that their circumstances are the result of individual choices, rather than flawed social policies and programs that reinforce inequality. These narratives shape the political economy, and as a result, inform misguided policies that exacerbate poverty in the United States rather than alleviate it.

As part of our Economic Justice portfolio, ideas42 is partnering with local community organizations across the U.S. to design and implement behaviorally informed campaigns to dismantle these harmful poverty narratives and uplift narratives that center dignity, agency, and equity instead. Critical to our narrative change efforts is better understanding the target audience for our campaigns. By analyzing national survey data, we identified distinct segments (or "subgroups") within the U.S. population, each with unique beliefs about poverty narratives. These insights enable us to customize messages for specific audiences and allocate resources efficiently across communication channels.

This report begins by summarizing our past research activities and describing the dataset we used to create these audience profiles. We then provide a detailed description of each profile uncovered and implications for our work.

Background and context

Building on previous research,[i] we focus on four key harmful and false narratives about poverty:

- **Welfare exploitation.** Social assistance programs encourage a culture of poverty, and benefits recipients may exploit the system for their own gain.
- **Meritocracy.** Poverty is a result of not working hard enough, and most people can succeed if they make the effort.
- **Paternalism.** Low-income people need guidance and supervision, from either the government or other actors.
- **Fatalism.** Poverty is a fact of life, and there's little anyone can do about it.

In addition to these harmful narratives, we also consider the structural narrative, which emphasizes the role of systems, institutions, and society in perpetuating poverty rather than the person experiencing it.

In 2021, we conducted a series of national and local surveys to measure the prevalence of harmful narratives and used this data to examine the demographic and psychological drivers of endorsement. For example, we found that Republicans and those with higher income showed less support for the structural narrative. However, simple associations like these are limited in creating targetable audience segments. They cannot speak to the full pattern of beliefs that people hold. There might be groupings along dimensions or at the intersections of identities (e.g. high income and less religious), that can be

[i] See Good Corporation (2019). Public Perceptions & Narratives Of Poverty In The U.S.; Feagin, J. R. (1972). America's welfare stereotypes. Social Science Quarterly, 921-933; and Yun, S. H., & Weaver, R. D. (2010). Development and validation of a short form of the attitude toward poverty scale. *Advances in Social Work, 11*(2), 174-187.

difficult to guess or appreciate. More advanced techniques like Latent Class Analysis (LCA) can identify such multi-dimensional patterns and divide respondents into groups with similar patterns.

Consequently, we conducted another national survey in 2023. Leveraging the larger sample size in this data set, we were able to conduct an LCA to identify distinct participant subgroups with different profiles of narrative beliefs. In addition to poverty narratives and participant demographics like race, income, and education level, these profiles also include an assessment of how receptive someone is to opposing viewpoints as an indicator of how amenable they may be to efforts to change their views and beliefs.

Data

The analysis in this report uses data from 2,879 individuals who completed our 2023 narrative change national survey. The survey probed endorsement of the five poverty narratives—***welfare exploitation, meritocracy, fatalism, paternalism, and structural***—by asking participants to rate their agreement with statements related to each narrative. For each narrative, we took a participant's average rating across statements and rounded that average, which allowed us to categorize whether a participant agreed, felt neutral about, or disagreed with each narrative.

To assess receptiveness to opposing viewpoints, participants rated their agreement with statements related to three aspects of receptiveness:

- **Intellectual curiosity** about opposing views. This included statements like, "I like reading well thought-out information and arguments supporting viewpoints opposite to mine."
- **Derogation** of those holding opposing views. This included statements like, "People who have views that oppose mine often base their arguments on emotion rather than logic."
- **Taboo** issues, or the belief that it is inappropriate to debate certain issues. This included statements like, "Some ideas are simply too dangerous to be part of public discourse."

Like the poverty narratives, ratings for each of the receptiveness sub-scales were averaged and categorized into agree, neutral, and disagree.

In addition to poverty narratives and receptiveness, the LCA incorporates the following information about each participant: age, gender, race/ethnicity, education level, income level, political ideology, religiousness, and experience with benefits.

Finally, our previous research found that the following psychological concepts, which we categorize as "worldviews", are strongly associated with endorsement of harmful poverty narratives. We therefore examine how each subgroup scores on these measures:

- **Social dominance orientation (SDO):** A person's opposition towards equality for everyone in society and their willingness to maintain (and increase) dominance of their group versus others.
- **Right-wing authoritarianism (RWA):** A person's tendency to submit to traditional authorities and values, as well as punish those who disagree.

- **Racial resentment (RR):** A person's agreement with the general sentiment that the primary reason for racial disparities is lack of effort by people of color.

See the Appendix at the end of this document for more information about our methodology, including how we selected the variables that went into the analysis and further details on how these variables are defined.

Audience segments and their narrative profiles

Our analysis identified a set of four segments, each embodying a distinct pattern of narratives about poverty. The graph below illustrates these patterns, showing the proportion of respondents within each segment who either agree or strongly agree with each narrative. In the four sections that follow, we describe each segment in greater detail. See the Appendix for the full breakdown of what percentage within each segment reported a given view or characteristic.

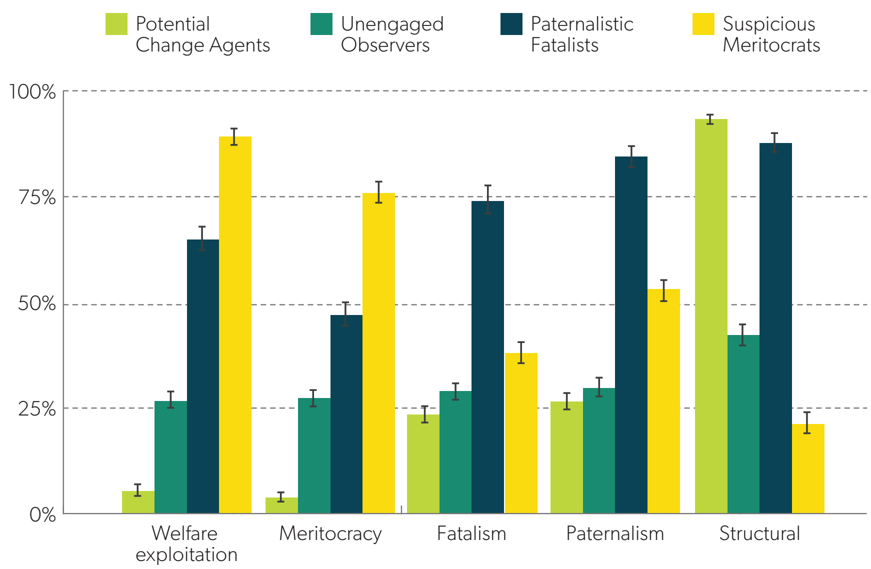


Figure 1. Agreement with poverty narratives by segment.

Segment 1: Potential Change Agents

The first segment constituted 27% of our sample. Of all the segments, they report the least agreement with the four harmful poverty narratives and overwhelmingly agree with structural explanations for poverty. This perspective, emphasizing the role of systems in perpetuating poverty rather than the person experiencing it, is most conducive to the promotion of effective social policy. We therefore name this group Potential Change Agents, highlighting their capacity to support and assist our narrative change campaign goals.

Potential Change Agents are relatively receptive to opposing viewpoints: they show high intellectual curiosity about such viewpoints (with 66.2% agreeing with the intellectual curiosity statements described above), and a lower tendency to derogate ideological opponents or dismiss certain issues as too taboo for public discourse compared to other segments.

Demographically, this group is predominantly female (66.4%) and non-Hispanic white (75.9%) but does have a notable representation of Black respondents (14.2%). Most find themselves in the middle-income bracket ($40,000 to $99,999) and live in households that receive or have received public benefits like Medicaid or unemployment (61.6%). Potential Change Agents are notable for their higher levels of education, being the only group where the majority hold at least a bachelor's degree, including a substantial 23.1% carrying advanced degrees.

Ideologically, this segment leans heavily liberal, and religion holds a smaller place in their lives compared to the other groups. Potential Change Agents also reject hierarchical and exclusionary ideologies, showing the least endorsement of social dominance, authoritarianism, and racial resentment of any subgroup.

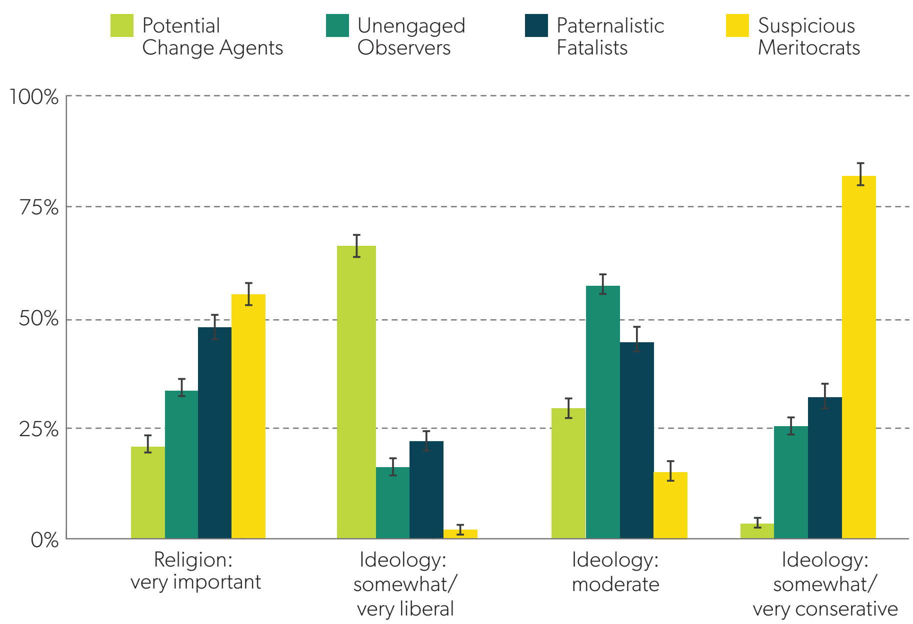


Figure 2. Religious and political views by segment. Potential Change Agents and Suspicious Meritocrats fall on opposing ends of the religious and political spectrum.

Segment 2: Unengaged Observers

Segment 2, making up 31% of our sample, is characterized by their neutral responses. Although they do not report high levels of agreement with any of the narrative statements (Figure 1), they do not report high levels of disagreement either, opting on average to "neither agree nor disagree" across harmful and structural narratives alike. For this reason, we call this group ***Unengaged Observers.*** Their neutrality across both the structural and harmful narratives may reflect an ambivalence or a measured distance from the debates surrounding poverty and social welfare.

This ambivalence may stem from a lack of engagement in debate or public discourse more broadly. When considering receptiveness to opposing viewpoints, Unengaged Observers show the lowest levels of agreement and the highest levels of 'neutral' responses across all types of receptiveness. This neutrality may suggest a preference to not participate in such discourse, or it could signal a sense of resignation or feeling of disenfranchisement from the prevailing social and political currents. Given this group's size, it is worth further investigation into whether their middling responses reflect genuine ambivalence or are based on feelings of disempowerment.[ii]

Unengaged Observers' centrist lens extends to their other ideological views. They are the most politically moderate segment and are most likely to report that religion is neither very important nor completely unimportant in their lives. The only ideology that deviates from this pattern is right-wing authoritarianism, for which 41.4% of this group report agreement, hinting at an undercurrent of traditionalism that might coexist with their otherwise centrist views.

Like Potential Change Agents, Unengaged Observers are predominantly female (65.1%), although they are more racially diverse (64.3% non-Hispanic white). Compared to the other segments, Unengaged Observers stand out for reporting the lowest socioeconomic status—almost half have a household income below $39,000, they show the lowest attainment of bachelor's or higher degrees, and seven out of ten members of this subgroup have had some experience with public benefits (Figure 3).

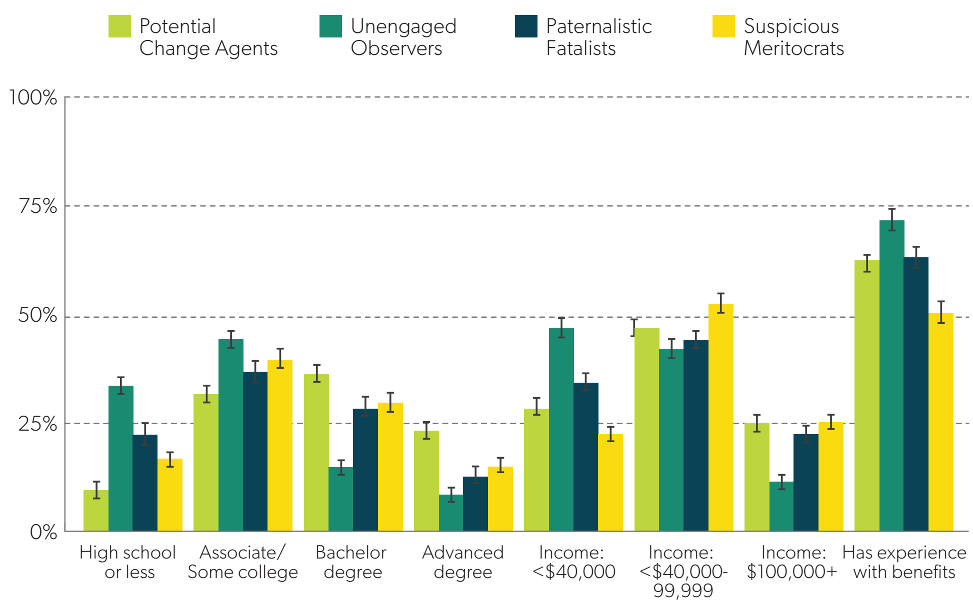


Figure 3. Socio-economic background by segment.
Note Unengaged Observers' lower levels of income and educational attainment, as well as their greater experience with public benefits.

[ii] One possibility we cannot ignore is that participants in this group may have simply been less invested in the survey itself, choosing to mark middle responses as the easiest option. Although we can never fully rule out validity-based interpretations like this, it is worth noting that Unengaged Observers were neither faster nor slower than the other segments in completing the survey, suggesting some level of comparability in terms of data quality and survey engagement.

Segment 3: Paternalistic Fatalists

Comprising 21% of our sample, our third segment reports markedly greater agreement with the harmful narratives than Potential Change Agents or Unengaged Observers, especially when it comes to fatalism and paternalism (see Figure 1). Crucially, these ***Paternalistic Fatalists*** also show strong agreement with the structural narrative. This suggests a perspective that emphasizes the role of systems in perpetuating poverty, but perhaps at the expense of personal agency or efficacy, leading to beliefs that poverty is an inevitable fact of society and that those experiencing it need guidance to make better choices.

When it comes to opposing viewpoints, members of this group report being intellectually curious about them (71.3% agreement), but also exhibit an elevated tendency to denigrate the proponents of these views or, in particular, dismiss them as inappropriate for public discourse (with 75.0% agreement of taboo-related statements). In line with these strong views on taboo issues as well as their high endorsement of paternalism, 58.7% endorse right-wing authoritarian statements, suggesting a marked affinity for traditional authorities and structured social orders.

Paternalistic Fatalists are the youngest (45% are under 44 years old) and most racially diverse segment in this study, with 22.6% identifying as Black and only 56.6% identifying as non-Hispanic white. They also include a diversity of socio-economic backgrounds, with more distributed representation across education and income levels compared to the other segments (see Figure 3). Politically they lean moderate (45.1%), but compared to Unengaged Observers this group has greater representation from both liberals and conservatives, consistent with their general mix of backgrounds. Paternalistic Fatalists are the second most religious segment, with nearly half (48.4%) considering religion very important in their lives.

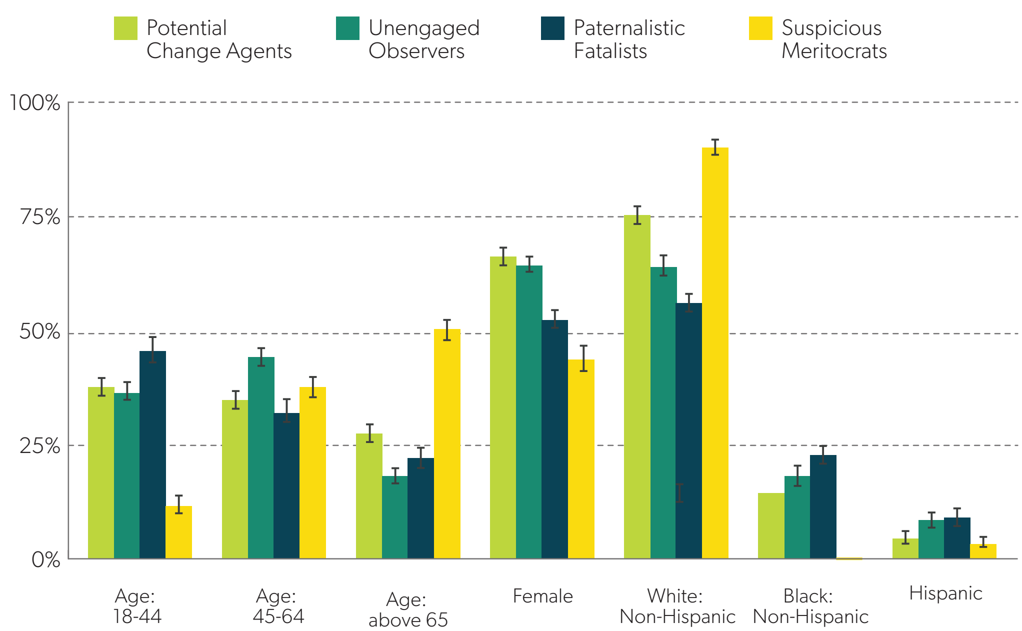


Figure 4. Demographic representation of each segment. Paternalistic Fatalists are the most racially diverse segment.

Segment 4: Suspicious Meritocrats

Finally, ***Suspicious Meritocrats*** account for 21% of our survey population. This group evinces a suspiciousness of people on welfare, highly endorsing the false belief that it is common for benefits recipients to exploit the system for their own gain. Coupled with high agreement with the meritocracy narrative and low agreement with the structural narrative (Figure 1), this suggests a view of poverty that places blame on the individual experiencing it, emphasizing personal accountability and viewing success as solely the result of individual effort.

Suspicious Meritocrats are by far the oldest segment, with 50.6% aged 65 or older, as well as the only group that is predominantly male. Nine out of ten members of this class are non-Hispanic white, making them the least racially diverse of the four classes.

Socioeconomically, this group includes the smallest proportion of individuals in the lowest income bracket (22.3%), with the majority in households that make between \$40,000 and \$100,000. They are also the least likely to have received any of the public benefits we asked about (see Appendix for full list), which may reinforce their beliefs in self-sufficiency and the potential for self-advancement without government aid.

Ideologically, Suspicious Meritocrats are the most religious (55.5% consider religion very important) and politically conservative (82.3%). Compared to the other segments, they contain the largest proportion of individuals who expressed agreement for social dominance (11.7%), racial resentment (71.4%), and right-wing authoritarianism (73.9%). This suggests a preference for traditional hierarchies, a lack of recognition of the role of systemic racism in perpetuating poverty, and a degree of skepticism towards social change, especially that which challenges their views on merit and personal responsibility.

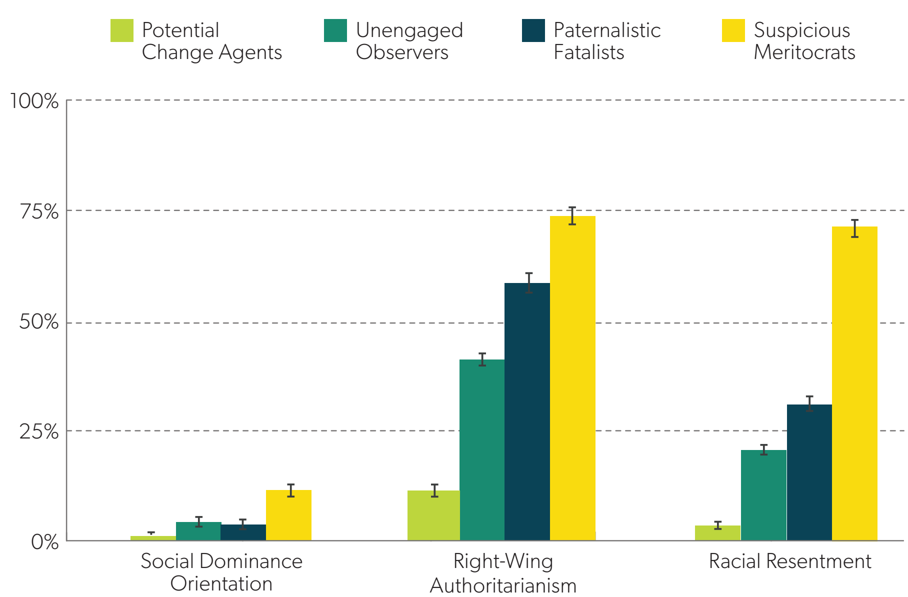


Figure 5. Agreement with worldviews by segment.
In addition to the variables included in the LCA model, we examined the proportion of each class who agreed with the "worldview" constructs. Suspicious Meritocrats stand out as showing the most endorsement of all of these constructs.

Where do we go from here?

Our narrative change initiatives are actively building behaviorally informed campaigns to dismantle harmful poverty narratives in cities across the U.S. As we develop these campaigns, we are anticipating how our designs may be differentially received by each segment uncovered in this analysis. For example, Paternalistic Fatalists and Unengaged Observers may interact very differently with a myth-busting media campaign.

We are also incorporating what we understand about these segments into our design choices. Would an initiative that takes aim at the most egregious aspects of the welfare exploitation narrative resonate with older white conservatives? How can we activate Paternalistic Fatalists' self-identity as being intellectually curious about views different from their own while treading carefully on topics that feel taboo or offensive? We are considering ways that our messaging could be tailored to resonate with each group and which communication channels are best suited to reach them.

In addition to being useful for tailoring and targeting, we plan to explore how these profiles can inform prioritization of limited resources. The receptiveness scales provide some indication of how responsive someone may be to narrative change efforts, but it is a limited proxy. As we launch and evaluate our narrative change campaigns, we will examine whether participants who have characteristics consistent with these subgroups show greater or lesser change, which can in turn provide stronger evidence about who is more receptive to such efforts.

This analysis deepens our understanding of audiences across the U.S. by incorporating not only demographic variables, but narrative patterns, ideological tendencies, and psychological preferences as well. With a richer, more concrete picture of who our work is and could be reaching, we are better equipped to dismantle harmful narrativers about poverty and shift the political economy towards a system that centers agency, dignity, and equity.

Appendix

A1: Results Table

Full results

	Potential Change Agents	Unengaged Observers	Paternalistic Fatalists	Suspicious Meritocrats	Average
Poverty Narratives					
welfare_agree	5.2%	27.0%	65.2%	89.2%	42.4%
welfare_disagree	63.5%	13.8%	2.7%	0.0%	21.8%
welfare_neutral	31.3%	59.2%	32.1%	10.8%	35.8%
meritocracy_agree	3.6%	27.1%	47.2%	76.2%	35.4%
meritocracy_disagree	82.1%	22.8%	25.2%	4.9%	35.4%
meritocracy_neutral	14.4%	50.2%	27.6%	18.8%	29.2%
fatalism_agree	23.1%	28.8%	74.0%	37.9%	39.0%
fatalism_disagree	30.3%	10.5%	2.0%	13.3%	14.6%
fatalism_neutral	46.5%	60.7%	24.0%	48.8%	46.4%
paternalism_agree	26.3%	30.0%	84.7%	52.8%	45.7%
paternalism_disagree	36.4%	21.2%	3.1%	15.4%	20.1%
paternalism_neutral	37.3%	48.8%	12.2%	31.9%	34.2%
structural_agree	93.6%	42.5%	88.0%	21.2%	61.6%
structural_disagree	1.9%	4.4%	0.6%	24.9%	7.2%
structural_neutral	4.6%	53.0%	11.3%	54.0%	31.2%
Receptiveness to Opposing Views					
curiosity_agree	66.2%	44.9%	71.3%	60.7%	59.6%
curiosity_disagree	7.4%	4.2%	2.6%	6.4%	5.2%
curiosity_neutral	26.4%	51.0%	26.0%	32.9%	35.2%
derogation_disagree	16.6%	17.2%	7.0%	8.2%	12.9%

	Potential Change Agents	Unengaged Observers	Paternalistic Fatalists	Suspicious Meritocrats	Average
derogation_agree	35.3%	12.0%	50.4%	52.4%	35.0%
derogation_neutral	48.1%	70.8%	42.6%	39.4%	52.1%
taboo_disagree	18.9%	11.5%	4.9%	11.7%	12.1%
taboo_agree	53.8%	34.4%	75.0%	60.9%	53.9%
taboo_neutral	27.4%	54.1%	20.2%	27.4%	34.0%
Participant Characteristics					
Age: 18-44	37.8%	37.0%	45.9%	11.9%	33.9%
Age: 45-64	34.5%	44.5%	32.2%	37.5%	37.7%
Age: above 65	27.7%	18.5%	21.9%	50.6%	28.4%
Female	66.4%	65.1%	52.8%	43.9%	58.3%
Male	33.6%	34.9%	47.2%	56.1%	41.7%
Asian / Pacific Islander	3.2%	2.2%	8.4%	2.7%	3.9%
Black + Non-Hispanic	14.2%	17.7%	22.6%	0.0%	14.1%
Hispanic	4.5%	8.1%	8.3%	3.0%	6.1%
Native American or Alaska Native	1.0%	1.5%	1.1%	1.0%	1.2%
Some other race	1.1%	6.3%	3.0%	3.1%	3.5%
White + Non-Hispanic	75.9%	64.3%	56.6%	90.2%	71.1%
Edu: advanced	23.1%	8.0%	12.7%	14.9%	14.5%
Edu: bachelor	36.0%	14.3%	28.4%	29.3%	26.3%
Edu: associate / some college	31.6%	44.3%	36.6%	39.7%	38.3%
Edu: high-school or less	9.3%	33.4%	22.3%	16.2%	20.9%
income: $100,000 or more	24.5%	11.4%	22.6%	25.3%	20.2%
income: 40,000 to 99,999	47.0%	41.6%	43.7%	52.4%	45.8%
income: below $39,000	28.5%	47.0%	33.8%	22.3%	34.0%
religion: neutral	42.4%	55.7%	37.8%	37.0%	44.4%

	Potential Change Agents	Unengaged Observers	Paternalistic Fatalists	Suspicious Meritocrats	Average
religion: not at all important	36.2%	10.0%	13.8%	7.5%	17.3%
religion: very important	21.4%	34.3%	48.4%	55.5%	38.3%
ideology: moderate	29.7%	57.6%	45.1%	15.7%	38.7%
ideology: somewhat or very conservative	3.7%	25.9%	32.5%	82.3%	33.1%
ideology: somewhat or very liberal	66.5%	16.5%	22.4%	2.0%	28.1%
benefit_exp: no	38.4%	28.2%	37.3%	49.5%	37.4%
benefit_exp: yes	61.6%	71.8%	62.7%	50.5%	62.6%
Worldviews[iii]					
SDO_agree	0.81%	4.55%	4.06%	11.66%	4.9%
SDO_disagree	92.03%	60.26%	59.56%	48.06%	66.13%
SDO_neutral	7.16%	35.2%	36.38%	40.28%	28.97%
RWA_agree	11.22%	41.38%	58.71%	73.85%	43.67%
RWA_disagree	75.95%	25.52%	21.32%	9.36%	34.85%
RWA_neutral	12.84%	33.1%	19.97%	16.78%	21.49%
RR_agree	3.24%	20.75%	31.3%	71.38%	28.71%
RR_disagree	79.05%	22.61%	28.76%	2.65%	34.99%
RR_neutral	17.7%	56.64%	39.93%	25.97%	36.3%

[iii] Note that the Worldview constructs were not included in the LCA directly, but were subsequently examined for endorsement among the four classes.

A2: Methodology

The analysis in this report uses data from the 2023 narrative change national survey, conducted between November 2 and November 7, 2023. This section covers the methodological framework employed in our cluster analysis of poverty narratives. The first subsection addresses our clustering methods and the choice of Latent Class Analysis (LCA), the technique used to identify distinct groups within our data. The second subsection covers the selection and definition of variables. Lastly, we discuss the determination of the number of classes, which is important for the robustness and interpretability of our clustering outcomes.

Clustering methods: Latent Class Analysis

The primary objective of our analysis was to identify data-driven population subgroups. To achieve this, we used Latent Class Analysis (LCA) as the most appropriate clustering analysis method to handle the nature and complexity of our data. LCA is a statistical method used to identify subtypes or classes within a population, which are inferred from individuals' responses to a set of observed variables. The core aim of LCA is to categorize individuals into mutually exclusive and collectively exhaustive groups that accurately encapsulate their similarities and differences with respect to the measured items. In this approach, each class is characterized by a unique profile of probabilities that signifies the likelihood of specific responses.

The analytical process of LCA involves estimating these probabilities, which, in turn, define the classes based on the distribution of the observed data. A key aspect of this method is the estimation of the LCA model through maximum likelihood estimation (MLE). The primary goal here is to identify the model parameters that most effectively maximize the likelihood of the observed data fitting the model.

One of the significant advantages of LCA, particularly in the context of our survey, is its ability to incorporate both categorical and continuous data, making it particularly well-suited for analyses involving mixed data types. This flexibility presents a distinct advantage over other clustering methods used in machine learning, such as k-means, which is generally more suited for continuous data. Unlike k-means, which assigns observations to clusters based solely on the mean values of variables, LCA accommodates the intricacies of mixed data types more effectively. This is particularly beneficial for survey data that includes socio-demographic and ordinal variables, where the relationship between variables may not be linear or uniform.

Moreover, LCA offers advantages over hierarchical clustering (HC). While HC is useful for visualizing data structure and does not require pre-specifying the number of clusters, it can be less practical for large datasets due to computational intensity and difficulties in determining the exact number of clusters. LCA, in contrast, provides a more structured approach to defining the number of clusters based on statistical criteria, making it more suitable for complex, multi-dimensional data like ours. Additionally, LCA is adept at handling missing data and measurement error, which is a common challenge in survey data. It assigns each observation to a specific cluster while indicating the probability of that membership, a feature not typically present in methods like HC. This probabilistic approach allows for a more nuanced understanding of the data, accommodating the uncertainty inherent in survey responses.

Variable selection and definition

Variable selection

In LCA, variables serve as indicators that help to identify patterns not directly observed in the data, allowing individuals to be grouped into categories or 'clusters' based on similarities in their responses. Selecting the variables that will go into a LCA is a critical step in the analytic process. Our approach to variable selection was systematic and data-driven, ensuring a robust and theoretically grounded analysis. For more details on the variables included in each tested specification, refer to the model comparison section of the supplementary tables provided below. The steps followed for selecting the relevant variables were the following:

1. **Initial Variable Pool:** We began by compiling a comprehensive list of potential variables from the survey, amounting to 35 in total. These variables were identified as potentially relevant to the analysis based on their theoretical and empirical significance in the context of poverty narratives.
2. **Prioritization of Variables:** Each variable was then assigned a level of priority based on theoretical considerations. The categories of priority were 'low', 'medium', 'high', and 'required' using the criteria below. This prioritization provided a structured framework for systematically incorporating variables into our analysis.
    - A. Required. This only included two constructs: The first was poverty narratives, as they are the subject of this analysis. The second was a measure of "dispositional receptiveness to opposing viewpoints", which was included as a potential indicator of how receptive someone may be to narrative change efforts.
    - B. High priority. Common demographic characteristics and ideological beliefs our previous work has identified as highly relevant to poverty narrative endorsement.
    - C. Medium priority. Psychosocial factors we hypothesized may be associated with poverty narratives which had potential utility for narrative campaign design (e.g. social connectedness).
    - D. Low priority. All other variables.
3. **Testing and Comparing Models:** With this framework in place, we tested a series of models to compare their fit. We started with a base model that included only the 'required' variables. Subsequently, we developed additional models by progressively including variables of 'high' (Model 1) and 'medium' (Model 2) priority. Additionally, for Models 1 and 2, we explored alternative specifications (1a and 2a) where some variables were recoded to reduce category numbers. This strategy aimed to simplify variables, enabling the inclusion of a broader range without compromising the model fit. A key challenge that we aimed to overcome at this stage was that incorporating a higher number of explanatory variables may enhance the model's theoretical comprehensiveness but can also limit its fit, as overly complex models risk overfitting and reduced predictive accuracy.

4. **Model Evaluation:** The models were then evaluated using the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC). While the most statistically robust model was the Base Model, we ultimately selected Model 1A based on theoretical grounds. This model included 'high' importance variables, deemed crucial for an in-depth understanding of subgroups in our data and for generating a solution that would be practically useful for our campaigns.
5. **Refinement of Model 1A:** From the foundation of Model 1A, we further refined our variable selection through eight additional models (1A to 1H), each varying in the number of categories for specific variables. We also assessed the impact of including or excluding certain variables on the model's overall fit.
6. **Final Model Selection:** The culmination of this process was the selection of Model 1F, which incorporated a balanced and theoretically coherent set of variables. These included poverty narratives, receptiveness, age group, gender, race, education, income, religious importance, political ideology, and experience with benefits. This model provided the most insightful and meaningful categorization of our survey respondents, aligning with our analytical objectives.

Variable definition

Survey items related to poverty narratives or receptiveness to opposing viewpoints were rated on a Likert scale from 1 to 5 where the options were Strongly disagree, Disagree, Neither agree nor disagree, Agree, and Strongly agree. To conduct the LCA, we took the average of all statements a participant rated related to a given construct (e.g. all statements related to fatalism). The average scores for each respondent were then rounded to the nearest integer and categorized into three response levels: 'agree' (scores 4 and 5), 'neutral' (score 3), and 'disagree' (scores 1 and 2).

The LCA also incorporated several variables that were not Likert ratings. Those variables were defined as follows:

- **Age:** Categorized into three groups: '18-44', '45-65', and 'above 65'.
- **Gender:** Recoded into two categories, 'Female' and 'Male'. Due to the small sample size (12 observations), observations from the "Other/Non-binary" category have been excluded.
- **Race/Ethnicity:** Classified into six categories: 'Asian or Pacific Islander', 'Black or African American + Non-Hispanic', 'Hispanic', 'Native American or Alaska Native', 'Some other race', and 'White or Caucasian + Non-Hispanic'. The Hispanic category includes all respondents of any race or ethnicity who identify as Hispanic. Observations marked as "Doesn't say" were excluded (16 observations).
- **Education Level:** Divided into four categories: 'High school or less', 'Associate / Some college', 'Bachelor', and 'Advanced'. Responses marked as "Prefer not to say" were excluded (23 observations).
- **Income Group:** Segmented into 'Below $39,999', '$40,000 to $99,999', and '$100,000 or more'.
- **Religious Importance:** Grouped into 'Not at all important', 'Neutral', and 'Very important'. The 'Neutral' category combines the 'Not too important' and 'Somewhat important' responses.

- **Political Ideology:** Grouped into 'Moderate', 'Somewhat or very conservative', and 'Somewhat or very liberal'. Responses marked as "Prefer not to answer" were excluded.
- **Benefit Experience:** A binary variable indicating whether anyone in the respondent's household has (1) or has not (0) received benefits (including SNAP, WIC, Medicaid, Public housing, TANF, unemployment, or other benefits) in the past or present.

Finally, in addition to the variables included in the analysis, LCA clustering allows us to assign a class to each observation in the data, and thus to assess how variables which were not included in the model are differentially distributed across classes. Based on their theoretical relevance, the presentation of results includes descriptives on how classes differed across racial resentment, right-wing authoritarianism and social dominance orientation, variables which we categorize as "worldviews" and which were not included in the model itself. These were composed of rated statements and categorized into 'agree', 'neutral', and 'disagree' in the same way as the poverty narratives and receptiveness scales.

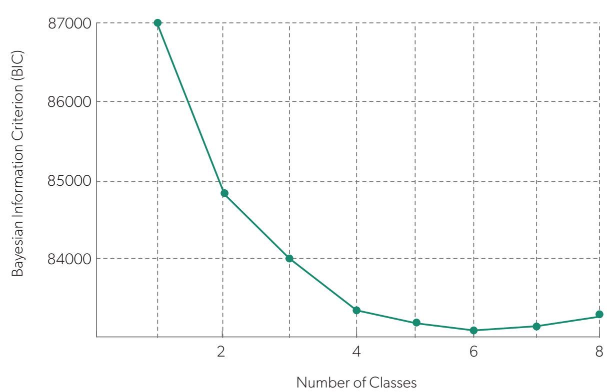
Number of classes

Determining the appropriate number of classes in LCA is a critical step that influences the validity of the interpretations drawn from the model. For this analysis, a range of one to eight classes was considered and ultimately a four-class solution was selected. To inform the final decision, several statistical criteria were examined: the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Average Latent Posterior Probability (ALPP), and Chi-Squared statistics, each providing insights into model fit and complexity.

Results are presented in an elbow plot form, which illustrates the relationship between the number of classes and the model's statistical criteria, where a decrease in these criteria indicates better model fit. Elbow plots are intended to show where the benefits of adding more classes start to diminish. This is often visualized as a 'bend' or 'elbow' in the plot, after which the decrease in the criterion value becomes less steep. The location of this bend helps in identifying the optimal number of classes, beyond which increasing complexity (more classes) does not yield proportional improvements in model fit.

The elbow plot for BIC (Figure A1) reveals a consistent decline as the number of classes increases, with a notable plateau or decrease in the rate of improvement beginning at four classes. This suggests that adding more classes beyond four would result in diminishing returns with respect to improving the model fit. This is consistent with the AIC, Chi-Squared, and ALPP results.

FIGURE A1. Elbow Plot of Bayesian Information Criterion (BIC) by Number of Classes



Crucially, beyond these statistical considerations, the four-class solution aligns with the theoretical objectives of this project. The classes derived from this model are highly interpretable and offer a meaningful differentiation between groups, which facilitates a nuanced understanding of the variables within our dataset. The decision to adopt a four-class model is, therefore, not solely based on statistical indicators but also on the theoretical coherence and interpretability of the classes. This balance of empirical evidence and theoretical alignment ensures that the model is both statistically robust and substantively meaningful, thus providing a solid foundation.

A3: Supplementary Tables

Model selection

TABLE 1. COMPARISON BY VARIABLE PRIORITY

	Priority level	AIC	BIC
Base model	Only required	34991	35301
Model 1	High priority	97563	98795
Model 1A	High priority	88178	89119
Model 2	Medium priority	128771	130116
Model 2A	Medium priority	113602	114810

TABLE 2. MODEL 1A VARIATIONS

Except for AIC and BIC, numeric values in the table below refer to the number of categories into which the variable was divided.

Model	1A	1B	1C	1D	1E	1F	1G	1H
AIC	88178	84609	86792	86187	80660	78209	78534	78946
BIC	89119	85419	87651	87021	81446	78947	79296	79708
welfare	3	3	3	3	3	3	3	3
meritocracy	3	3	3	3	3	3	3	3
fatalism	3	3	3	3	3	3	3	3
paternalism	3	3	3	3	3	3	3	3
structural	3	3	3	3	3	3	3	3
receptiveness	3	3	3	3	3	3	3	3
age_group	4	3	3	3	3	3	3	3
gender_l	3	2	2	2	2	2	2	2
race_full_l	7	6	6	6	6	6	6	6
education_l	5	4	4	4	4	4	4	4
income_group	4	3	3	3	3	3	3	3
employment_l		4	4	4	4		4	4
reli_imp_l	4	3	3	**4**	3	3		3
poli_imp_l	6	3	**5**	3	3	3	3	
benefit_exp		**2**	2	2		2	2	2

Sample size for all LCA variables

Poverty narratives

	welfare exploitation	meritocracy	fatalism	paternalism	structural
agree	1223	1012	1103	1307	1772
neutral	1028	843	1358	1005	900
disagree	628	1024	418	567	207

Receptiveness scales

	curiosity	derogation	taboo
agree	1711	995	1548
neutral	1016	1517	988
disagree	152	367	343

Socio-demographics

	Category	n
Age group	Age: 18-44	962
	Age: 45-65	1086
	Age: above 65	831
Gender	Female	1683
	Male	1196
Race/ethnicity	Asian or Pacific Islander	115
	Black or African American + Non-Hispanic	394
	Hispanic	172
	Native American or Alaska Native	32
	Some other race	102
	White or Caucasian + Non-Hispanic	2064

	Category	n
Education	Advanced	422
	Associate / Some college	1095
	Bachelor	758
	HS or less	604
Income	$100,000 or more	557
	$40,000 to $99,999	1261
	Below $39,999	937

Other variables

	Category	n
Religious importance	Not at all important	494
	Neutral	1276
	Very important	1109
Ideology	Somewhat or very conservative	962
	Moderate	1119
	Somewhat or very liberal	798
Benefit experience	0	1084
	1	1795

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