DIFFERENCES IN CATEGORIZATION STRATEGY BETWEEN CONSERVATIVES AND LIBERALS

by
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A THESIS

Presented to the Department of Psychology & Political Science
and the Robert D. Clark Honors College
in partial fulfillment of the requirements for the degree of
Bachelor of Science

May 2025

An Abstract of the Thesis of

Ashish Sathya for the degree of Bachelor of Science
in the Department of Psychology & Political Science to be taken June 2025

Title: Differences in Categorization Strategy between Conservatives and Liberals

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Evidence has shown that liberals and conservatives' political beliefs govern where they live, relationships, and social identity. Despite that, there has been little work into the cognitive differences between political affiliations. One domain that shows large individual differences in cognitive styles is categorization; people usually fall under one of two strategies – prototype, focusing on the central features of an object, or exemplar, focusing on the specific different representations of an object. This study examines, using 2 experiments, if liberals and conservatives have different categorization strategies. To assess political typology in experiment 1, we used the Pew Political Typology survey and found no relationship between strategy used and affiliation. However, very few participants scored in the conservative range, which suggested that the measure lacked validity. In experiment 2, I used the Social Economic Conservatism Scale, another political affiliation measure, and found that the more conservative someone scored, the more likely they were to use a prototype categorization strategy, whereas the more liberal someone scored, the more likely they were to use an exemplar strategy. This paper exemplifies the need for more research to be done in political psychology to understand the cognitive differences between liberals and conservatives.

Acknowledgements

First, I would like to thank Dr. Dasa Zeithamova, Troy Houser, Cheyna Warner, and everyone else in the Brain and Memory lab for taking a chance on me to explore my niche interest in political psychology; without the support from them this project wouldn't be possible. I would also like to thank my CHC representative Dr. Anita Chari, whose support from HC 477 carried throughout my senior year while I was working on my thesis.

Finally, I want to thank those outside of the academic environment; my parents for constantly pushing and supporting me through thick and thin and my friends who were a rock for bouncing ideas off and ensuring that I would finish this thesis in due time.

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Introduction

Polarization is increasing within the western world (Silver, 2022). Nearly 85% of adults in the United States believe that political debate has become less respectful, less fact-based, and less substantive (Dunn, 2019). There are significant problems associated with the increasing polarization – mainly people's tolerance for the opposite viewpoint. As such, researchers have found that political beliefs are able to predict romantic relationships as people prefer to be in a relationship with someone who has the same political beliefs, and impacts patterns of residential selection (Huber & Malhotra, 2017; Motyl et al., 2014). Additionally, political beliefs impact leaders' abilities to effectively develop policy, due to the fact that political actors (politicians, pundits, donors, etc) are likely to suffer from confirmation bias, looking for information that already supports their viewpoints (Frimer et al., 2017). The worst consequence of the increasing political polarization is that the risk of political violence, the insurrection that occurred on January 6th, 2021, largely occurred because of a perfect storm of misinformation alongside with increasing polarization (Kleinfeld, 2021; Sadri & and Roberts, 2023).

To help deal with this pressing matter, psychologists have examined the social mechanisms that drive polarization. Bavel & Pereira (2018) examined the role of the Social Identity Theory, when people define their individual status in relation to their social classification – specifically regarding their political affiliation. Researchers found that this social classification becomes so intense that political actors will place party loyalty over the truth itself, aiding the increase in polarization. Cassino & Erisen (2010) examined the role of priming voters before making a political choice, such as voting, and found choices were impacted after being presented with negative information about a specific candidate. It appears as if people are fickle in the political process, and that information that is shown to them prior to voting has more influence rather than determining if someone is a good fit for the positions they value. Without understanding the cognitive differences between political affiliations, efforts to mitigate political polarization will not be as effective.

As mentioned before, research in political psychology typically focuses more on the social underpinnings with little attention paid to how cognitive factors impact political thinking. In recent years, investigating political cognition has become more common. For example, Conway III et al. (2016) examined the differences in attention in conservatives and liberals when viewing headlines of news stories. They found that conservatives attended to more specific details while liberals paid more attention to the bigger picture of headlines.

Previous work has also examined partisan difference in cognition on the neural level, such as risk-taking (Schreiber et al., 2013). When measuring risk-taking in both liberals and conservatives, researchers found that in liberal participants, the left posterior insula was activated during risk-taking behavior. This brain region is involved in the theory of mind, which refers to our ability to perceive others as thinking organisms. Conservatives showed risk-taking-related activation in the right amygdala, a region responsible for regulating emotional processes (Schreiber et al., 2013). Researchers see this as evidence for distinct neural processes between conservatives and liberals which could reflect a multitude of distinct values – issues, candidates, and policy positions.

This neural link have had researchers to ask questions to understand how political actors learn new information, to help develop better practices when attempting to teach said information. For example, someone holding political biases of a member of a stereotyped group. Those biases might be difficult to change over time because of the representations stored within someone's memory of that stereotyped group (Lieberman et al., 2003). Previous work provides a foundation for exploration of political cognition, as marked partisan differences have been identified.

Learning is a broad concept so the method of operationalizing it will be via category learning, an important idea in how humans acquire knowledge. It is a principle that involves linking information together with a shared term or label (Zeithamova et al., 2008). These category representations have shown to affect perception of related information, aiding people in learning new information, and helping people quickly make decisions (Koriat & Sorka, 2015; Murphy & Allopenna, 1994; Van Gulick & Gauthier, 2014). Category learning has been showed to play a role in emotional recognition, and social biases (Etcoff & Magee, 1992; Liberman et al., 1957; Smith & Zarate, 1990), which are critical factors in political behavior. However, most important principle to come from category learning is the ability to apply previously learned information to novel situations never experienced or seen before (Zeithamova et al., 2008).

Two strategies that people often employ in category learning are prototype and exemplar. The exemplar model is a method of categorization where individual members of a category are compared to specific examples of that category. For example, when thinking of a dog, an exemplarist may imagine specific dogs that have been seen before - a neighbor's poodle, a picture of a Golden Retriever, or their own German Shepherd. When that exemplarist sees a brand-new animal out in the wild, they may compare that new dog to the *specific*, previously encountered, dogs to conclude that animal is a dog. On the other hand, the prototype model generates a more general, abstract representation of a concept, and would represent a dog with its *average* features - a tail, fur, nose, ears, etc. When examining a dog in the external world, the prototypist would compare it to the abstract representation – a furry creature, with a tail, nose, and ears – to conclude it is a dog. This concept may shed light on how we may represent political actors. For example, when discussing a "progressive" people may think of a certain political figure (i.e. Senator Bernie Sanders from Vermont), or they may be thinking of broad policies that a progressive person would advocate for (i.e. Medicare for all).

However, of the few studies that do engage with political cognition, few span the entire political spectrum, often not having a large sample of conservatives (Cassino & Erisen, 2010; Conway III et al., 2016; Frenda et al., 2013). The majority of this research lacks a sufficient number of conservative participants and does not leverage a standardized scale of partisanship across studies. Aside from the sampling problems, the method of political identification could be stronger. Previous studies created their own measure of affiliation not found in any Political Science literature. One study had participants self-identify themselves in one of three separate categories – conservative, moderate, and progressive, another study had participants ranking a seemingly arbitrary list of topics based on their level of agreement with it, and finally one study matched up publicly available voting data to determine participants' affiliation (Castelli & Carraro, 2011; Frenda et al., 2013; Schreiber et al., 2013). Here, I utilized better measures of political affiliation based on the available Political Science literature.

My main hypothesis is that conservatives and liberals differ in their cognitive styles, where conservatives focus more on individual details whereas liberals focus on the overall picture. Supporting this, researchers have examined the different views developed from political stories (Conway III et al., 2016). Conway III et al. (2016) found that participants became dogmatic, or unwilling to lay down their opinions, based on the political bend of the story. What was more interesting was the variation in focus while examining political stories – conservatives were more swayed by the small, specific, details when developing subjective ratings, whereas liberals were more focused on the bigger, more abstract, picture.

I will test this hypothesis by measuring political affiliation using the Pew Political Typology Survey and the Social Economic Conservatism Scale and cognitive style using individuals' categorization strategy.

Experiment 1

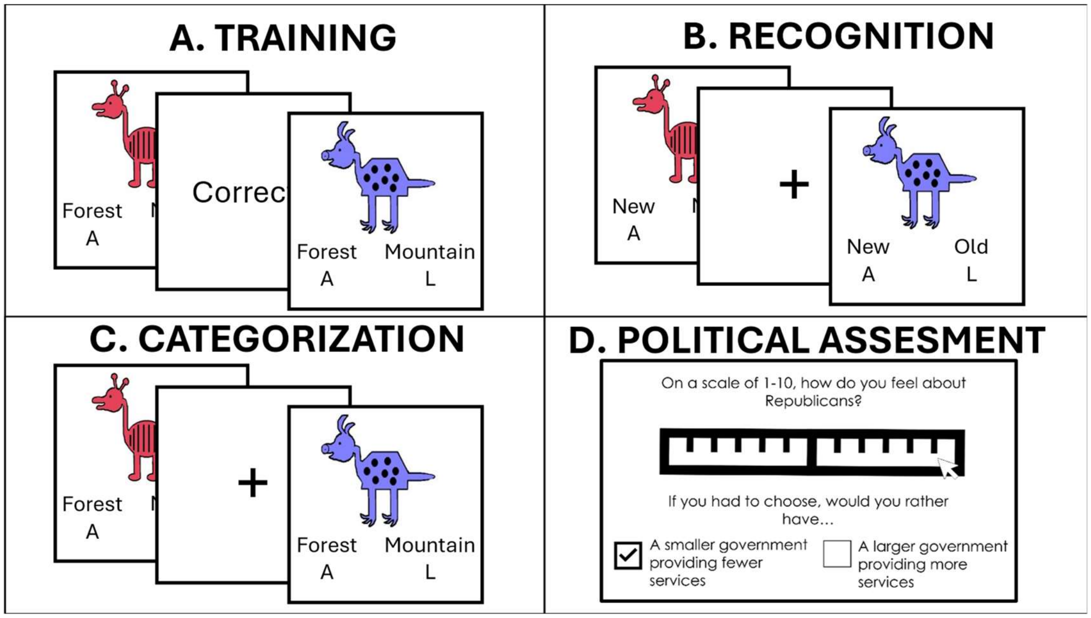
Methods

Participants

A total of 91 participants were recruited, ages 18-22 (68 female, 20 male, 3 non-binary, *M*age = 18.75, *SD* = 0.95) from the UO Human Subjects Pool and were given course credits for their participation. Of those, there were 2 participants who did not effectively complete the study and were excluded from the data because of technical complications. This left 89 participants, ages 18-22 (67 female, 19 male, 3 non-binary, *M*age = 18.75, *SD* = 0.96) for the final data analysis.

Experimental Design

Figure 1 Experimental Design



Note: This figure shows the tasks and order of tasks that participants went through during the study. A) Training – Participants categorized stimuli in the preferred location all whilst given feedback. B) Recognition – Participants determined if stimuli presented are either brand new or have already been seen (old). C) Categorization – Participants completed the same as training but without feedback. D) Political Assessment – Participants completed a survey to find their Political Affiliation.

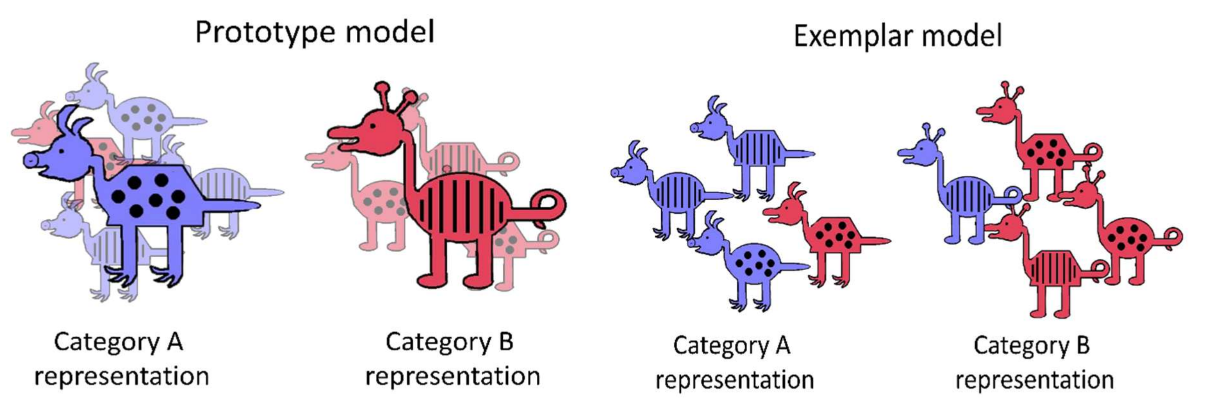
This study was an hour-long computer task conducted in an isolated room to minimize distractions. The study was comprised of 4 phases – training, recognition, categorization, and political affiliation survey (*Figure 1)*. I detailed these phases, and the materials used next. Importantly, recognition always came before categorization to ensure that there would be as little interference (new stimuli disrupting how well someone remembers or processes earlier information) as possible from the new stimuli presented during the generalization phase.

Materials

The stimuli were cartoon animals that vary along eight different binary attributes: color (purple/red), ear shape (straight/bulb), nose shape (snout/beak), neck size (short/long), shapes on the body (dots/lines), body shape (pentagonal/circular), foot shape (pointed/round), and tail size (short/long) (*Figure 2*). Two stimuli that have the exact opposite binary attributes served as the prototypes (the stimuli that bear the central tendencies across exemplars within a category), and these prototypes will be placed in a randomly selected category, which inform which category stimuli that share similar features will be placed in. This means that stimuli that are in Category A have more shared features with Prototype A than Prototype B and vice versa.

Training

Figure 2 Examples of Prototypes and Exemplars



Note: Representation of the Prototypes and Exemplars in the Stimuli.

The set size for training was eight stimuli, four falling in Category A, and the other four falling in Category B. As seen by *Figure 2*, the Category A and B exemplars differed from their prototype by about two features. Each participant was trained on those eight stimuli across 5 blocks. A block consists of 40 trials (8 training exemplars x 5 repetitions) shown in random order within each repetition.

On each trial, participants were told to sort the animals, the exemplar stimuli, into their preferred habitat (forests or mountains). The categories determined which habitat the stimuli preferred. For example, stimuli belonging to Category A may prefer forests over mountains, and stimuli belonging to Category B may prefer mountains over forests. Critically, participants were not shown the prototypes to potentially construct those attributes from the training stimuli without learning the prototype. They were given feedback on whether their choice is correct or not, which gave them encouragement for them to continue learning the pattern of the stimuli. Each trial began with presentation of a single training stimulus in the center of the screen, after which participants were prompted to choose whether the stimulus belongs in Category A or Category B by pressing “a” or “l”, respectively, on the keyboard. Responses were self-paced. After a response, corrective feedback was presented for 1s, followed by a 0.5s fixation cross before start of the next trial.

Recognition

As seen by Figure 1, each trial begins with showing the stimulus in the center of the screen, after which participants are prompted to choose whether the stimulus is “old” (meaning it was shown during training) or “new” (meaning it was not shown during training). Responses were self-paced and followed by a 0.5s fixation cross before beginning the next trial. This phase consisted of one block, with the 56 stimuli being randomized across participants. In addition to the training stimuli, participants were shown: 16 novel stimuli with 5 shared features, 16 novel stimuli with 6 shared features, and 16 novel stimuli with 7 shared features that were all shown once. Stimuli were presented in a random order and in a single block.

By endorsing stimuli that are closer to the prototype as old when it is in fact new, participants are extracting out a prototype from the training stimuli. If participants have a high corrected hit-rate (Proportion of Hits (Correct Answers/Total Stimuli) – Proportion of False Alarms (Wrong Answers/Total Stimuli)), meaning they are able to distinguish old training stimuli from new stimuli, it would indicate that they formed a strong exemplar representation.

Generalization

The generalization task uses the same stimulus set as the recognition task (one block of 56 randomly ordered trials). Participants were instructed to categorize the stimuli into Category A or Category B. Responses were self-paced and followed by a 0.5s fixation cross. Additionally, no feedback was provided during the generalization task.

Pew Research Typology Survey

The political survey used in experiment 1 was the Pew Research Political Survey. The survey was developed by the Pew Research Center, which has been gauging public opinion issues since its founding in 2004. The Typology Survey, which was created at the center's founding, has been updated every few years to capture major political shift.

Despite how often it has changed, the Pew Research Typology survey has been used as a reliable measure of political affiliation for multiple studies. For example, Anderson and Zyhowski looked at how the preference for the 2016 election would be influenced by how eighth graders scored on the political typology survey, specifically interested in how their score on the typology survey would change their political socialization (Anderson & Zyhowski, 2017). Students then took the typology survey to categorize them into the eight subfields that lie within the conservative to liberal political spectrum (Anderson & Zyhowski, 2017). Simmions and Simmions also examine the usefulness of the Pew Research typology survey, explaining that the typology survey intertwines political affiliation theory with statistical techniques to produce an effective way of grouping political affiliations (Simmons & Simmons, 2008). This survey was given to participants after they are done with the Training, Recognition, and Generalization tasks to group participants politically.

Statistical analysis

Training

To ensure that participants successfully learned the category memberships of the training stimuli, I will first calculate each individual's average categorization accuracy during training and compare it to chance (50%) with a single sample t-test.

Generalization

To ensure that participants could successfully generalize the category knowledge acquired during training to never-before-seen stimuli, I will calculate each individual's average categorization accuracy during the generalization phase and compare it to chance (50%) with a single sample t-test.

Recognition

To measure the extent to which participants could successfully recognize training stimuli, I calculated the corrected hit rate for each participant. Corrected hit rate is the proportion of hits minus the proportion of false alarms, where a hit is responding "old" to an old, or training, stimulus, and a false alarm is responding "old" to a novel stimulus. This measure of recognition is preferred over the mere average of hits because the average of hits does not control for the possibility that an individual was responding "old" to all, or most, stimuli. I will compare corrected hit rates to chance (0) with a single sample t-test.

Political typology

The Pew Political Typology was scored by first hand-coding responses, such that liberal values were positive and conservative values were negative. For example, one of the survey questions reads, “If you had to choose, would you rather have…” with the following response options: (1) “A bigger government providing more services”. and (2) “A government providing fewer services”. For this question, (1) was coded as 1 and (2) was coded as -1. This allowed us to then average across responses. This measure was treated as a scale, with positive and negative denoting liberal or conservative. The higher, or lower, someone scored indicated the strength of beliefs A participant with a positive average score was labeled a liberal and a participant with a negative average score was labeled a conservative.

Relationship between generalization strategy and political typology

To answer our main question, which is whether the strategy that people use to generalize concept knowledge, differs between conservatives and liberal, I first obtained strategy assignments for each participant. I fit prototype and exemplar models to the trial-by-trial responses from the generalization phase for each participant. Notably, prototype models assume category structures are represented by their prototype. As such, the similarity of each generalization stimulus and the two category prototypes is first computed via an exponential decay function, while taking into account differences in attention to specific attributes. For example, the similarity of generalization stimulus x to prototype A is

$$S_A(x) = \exp\left[-c \sum (w|x - proto_A|^r)^{\frac{1}{r}}\right],$$

where c is a sensitivity parameter controlling the rate at which similarity declines with distance, w is a vector of attention weights, and r is the distance metric (here, set to 1 to reflect city-block, or Manhattan, distance).

Exemplar models assume that categories are instead represented by their exemplars, or individual training stimuli. These models compute similarity between each generalization stimulus and every training stimulus and then sum the similarities within each category:

$$S_A(x) = \sum_{y \in A} \exp\left[-c(w|x-y|^r)^{\frac{1}{r}}\right],$$

where y is a training stimulus from Category A. All other parameters are the same as in the prototype model. Thus, both exemplar and prototype models make use of 9 participant-specific free parameters.

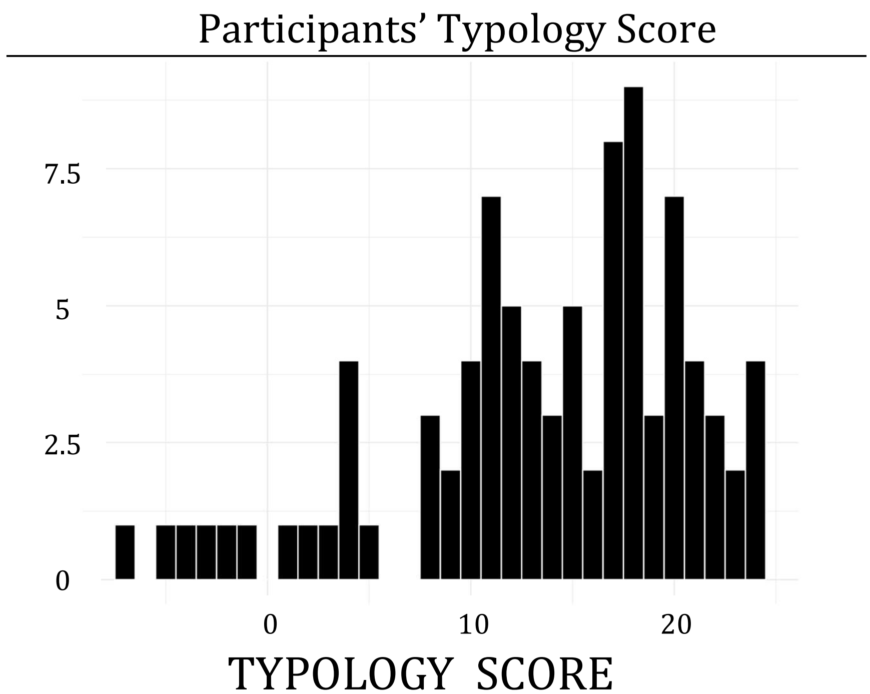
To transform similarities to response probabilities, we used the following response rule:

$$P(A|x) = \frac{S_A(x)}{S_A(x) + S_B(x)}.$$

Using the above equations, I obtained best fitting parameter estimates per participant per model via maximum likelihood estimation by minimizing the negative log likelihood with gradient descent.

Next, to determine whether a given participant relied on prototypes or exemplars when generalizing concept knowledge, we utilized a robust method for model selection known as Monte Carlo sampling. Each participant was assigned one of four strategy labels: prototype, exemplar, comparable, or random. First, I shuffled empirical responses 10,000 times per participant and fit prototype and exemplar models to the randomized response data to obtain a null distribution for both models. Then, I compared empirical model fits against the subject-specific null distribution for both models. If the empirical fits were better than 95% of the simulated fits, we conclude that the model describes the data better than assuming that the participant responded randomly. If neither prototype nor exemplar fit reliably better than chance, the participant was labeled “random”. To test for differences in model fits, I computed relative model fit differences $((fit_{proto}-fit_{exe})/(fit_{proto}+fit_{exe}))$ and compared them to relative model fit differences of the simulated fits per participant. One model was deemed a winner if the empirical fit differences appeared by chance with a frequency of <25% (Bowman et al., 2020; Bowman & Zeithamova, 2018). If both models fit equally well, the participant was deemed "comparable".

Figure 3



Note: Histogram of Participants' Political Typology Score. The higher the number the more liberal the participant is.

Results

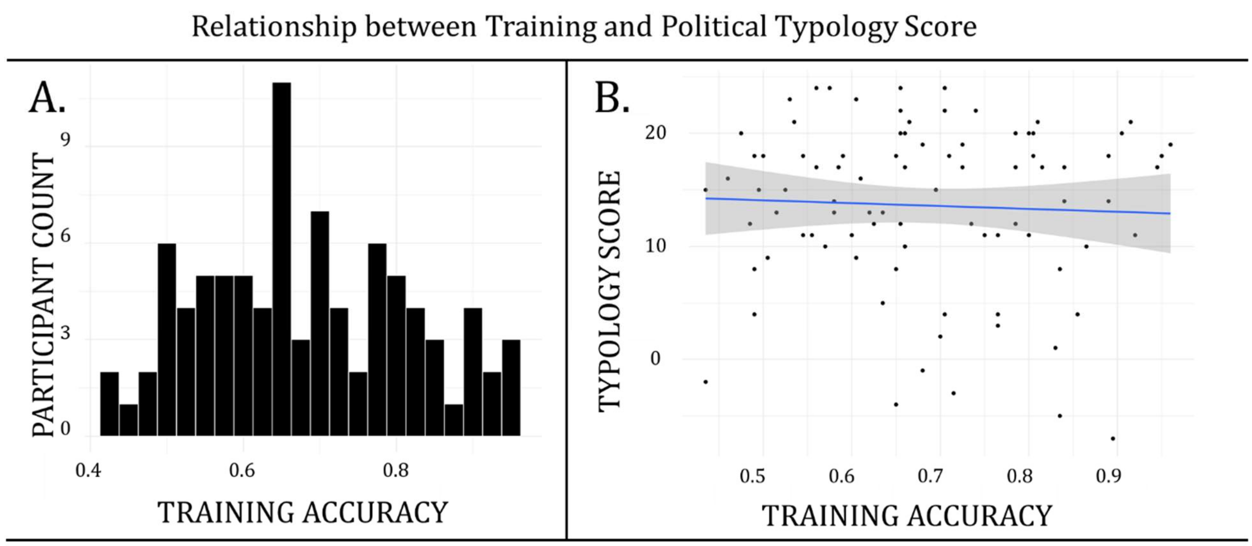
Political Typology

The Pew Political Typology was scored by making people who had a positive number liberal and those who had a negative number conservative. With this, nearly all participants were scored as being liberal, with only five participants being scored as conservative (M = 13.61, SD = 7.24; *Figure 3*). This discrepancy caused a change in how we separated the affiliation categories – instead of having a distinct conservative or liberal, the pew political typology was used as a continuous variable where a higher score indicated a more liberal participant.

Training

While being trained on the exemplars, most participants performed above chance (*M* = 0.68, *SD* = 0.13, $t(88) = 12.74$, $p < .001$; *Figure 4A*). The data suggests that participants were able to learn the categories to a moderate degree of success. When correlating participants' training accuracy to the typology score, Pearson's r is close to 0 ($t(87) = -0.44$, $r = -0.04$, $p = .661$; *Figure 4B*). Therefore, we found no relationship between category learning accuracy and the degree to which a participant endorsed liberal values over conservative values.

Figure 4



Note: A) Performance of Training task for Participants in Experiment 1. *B)* Correlation between Training Accuracy and Typology Score.

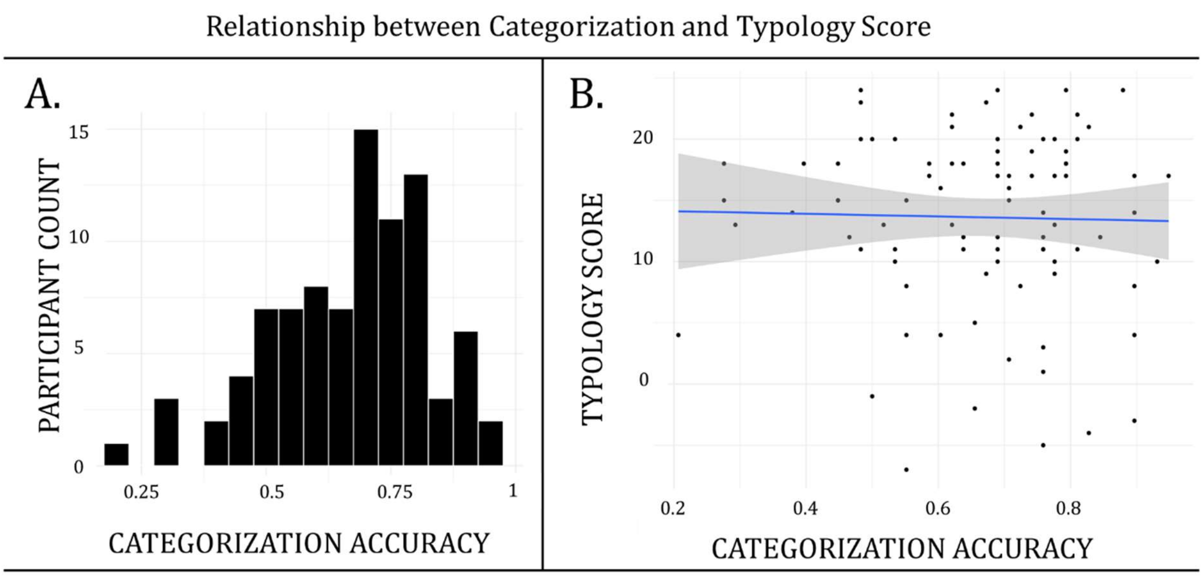
Recognition

When examining participants' corrected hit rate, it ranged from -0.5 to 0.5, with a majority of participants scoring near 0 (*M* = 0.05, *SD* = 0.20). Nevertheless, the average of 5% was reliable above chance ($t(88) = 2.54$, $p = 0.012$). When examining the correlation between corrected hit rate and typology score, the corretion was weak and negative, as well as not significant ($t(87) = -0.98$, $r = -0.10$, $p = .330$; *Figure 5*).

Generalization

Participants performed above chance during the categorization task (*M* = 0.66, *SD* = 0.15, $t(88) = 9.84$, $p < .001$; *Figure 6A*). This pattern suggests that participants were able to learn the categories and the location that the stimuli preferred in the absence of feedback showing overall. When examining the relationship between categorization accuracy and typology score, there was no correlation ($t(87) = -0.21$, $r = -0.02$, $p = .828$; *Figure 6B*).

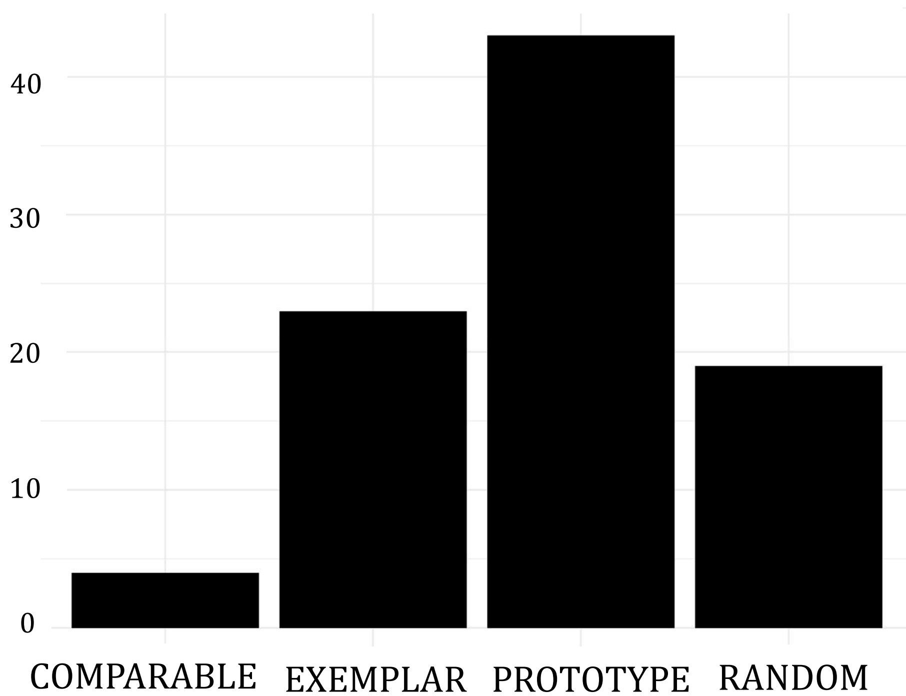
Figure 5



Note: A) Performance of Categorization task for Participants in Experiment 1. *B)* Correlation between Participant's categorization performance and Typology Score.

Figure 6

Bar Graph detailing strategies from Experiment 1



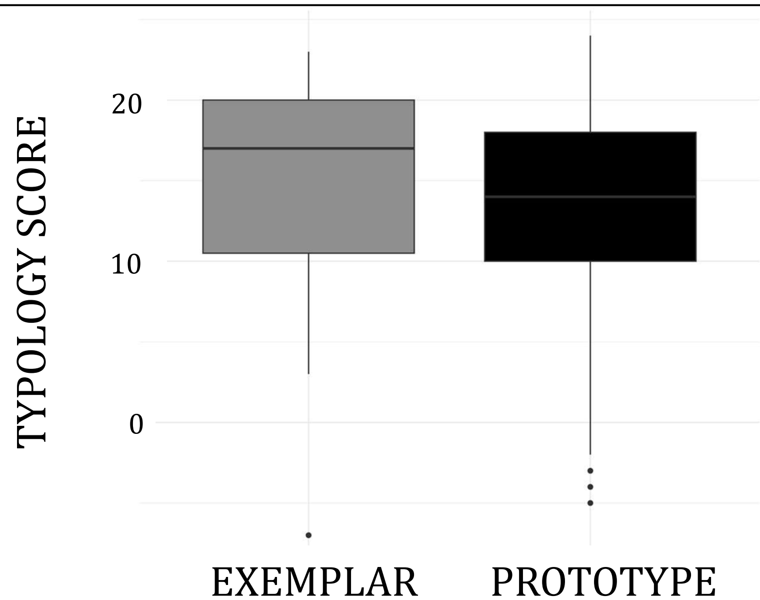
Note: Categorization strategies from Experiment 1.

Interactions between Political Typology & Categorization Strategy

Almost half of participants had a prototype categorization strategy, with a little over a quarter of them using an exemplarist strategy (*Figure 7)*. The rest of the participants used a random or comparable strategy, and were subsequently removed from the sample when examining the interaction between participants' typology score and categorization strategy. When examining the interactions between participants' political typology score and their categorization strategy (n=66), it appeared there were no significant findings between typology score and categorization strategy (Mprototype = 12.95, Mexemplar = 14.08, SDprototype = 7.65, SDexemplar = 7.75, $t(45) = 0.56$, $p = 0.57$; *Figure 8*). Therefore, categorization strategy and political typology did not appear to be related in this sample.

Figure 7

Boxplot with Typology Score and Generalization Strategy Used



Note: Graph showing there is no difference in strategy based on Typology Score.

Discussion

Experiment 1 revealed that typology score was not significantly related to participant's categorization strategy or performance in tasks. Moreover, there was a problem with sampling, with only 5 of the 89 participants being scored as conservative. To work through this, I changed the analysis from political affiliations to a continuous one using the typology score and correlating that with performance of the tasks. In the survey, there were questions asking participants feel about Republicans and Democrats, with the more warmly they felt about Democrats being scored as a liberal response and vice versa for the Republicans. However, the majority of participants felt negative about both. This finding is consistent with current research on anti-establishment thinking, given that around the globe, there is an decreasing sentiment regarding the political establishment class (Meyerson, 2020).

To solve the aforementioned problem, I conducted a second experiment, focused on looking for a new, more reputable, political survey compared to the one used in Experiment 1.

Experiment 2

Experiment 1 did not find a relationship between strategy and political affiliation, but the typology test used to find affiliation appeared to lack validity. Therefore, I replicated the experiment while introducing self-identification and a new political typology measure for further validation.

Methods

A total of 99 participants were recruited ages 18-29 years old (76 female, 20 male, 3 non-binary, *M*age = 19.20, *SD* = 1.76) from the UO Human Subjects Pool and were given course credit for participation. Of those, there were 24 participants who did not effectively complete the study and were excluded from the data because of technical complications. There was 1 participant who was excluded for political affiliation, as they were the only one person who rated themselves as independent, which is consistent with prior literature. This left 73 participants, ages 18-29 years old (59 female, 13 male, 1 non-binary, *M*age = 19.17, *SD* = 1.70) for the final data analysis.

Materials

The materials used for experiment 2 were the same as used in experiment 1, aside from the Pew Political Typology Survey which was replaced with two additions - the Social Economic Conservatism Scale and a political typology self-identification question.

Social Economic Conservatism Scale (SECS)

The SECS has several advantages when compared to the Pew Research Typology. For starters instead of participants answering different questions about social, economic, and political beliefs, the SECS survey aims to provide participants' feelings on certain broad subjects

(*Abortion, Limited Government, Military and National Security, Religion, Welfare Benefits, Gun Ownership, Traditional Marriage, Traditional Values, Fiscal Responsibility, Business, The Family Unit, Patriotism).* Participants were instructed to indicate how positive or negative they feel about a particular topic, with 100 being the most positive and 0 being the most negative, with participants receiving a final score in the end. The higher the final score, the more conservative a participant is. The scale was made by Everett, to standardize how researchers would be collecting political affiliations (Everett, 2013). As mentioned before in the introduction, a big problem when conducting political psychology research is operationalizing participants' political beliefs – as every paper did it a different way. The SECS is this study's method of gauging participants' political affiliations (Everett, 2013).

Self-Identification

Participants were prompted to self-identify their political affiliation by choosing the affiliation (Liberal, Conservative, and Independent) that fits them the best, which combined with SECS score will provide an accurate look at their political affiliation.

Experiment design and procedure

Experiment 2's design and procedure will mirror experiment 1, aside from the Pew Typology Test, which will be replaced with the SECS and Self-Identification.

Statistical analysis

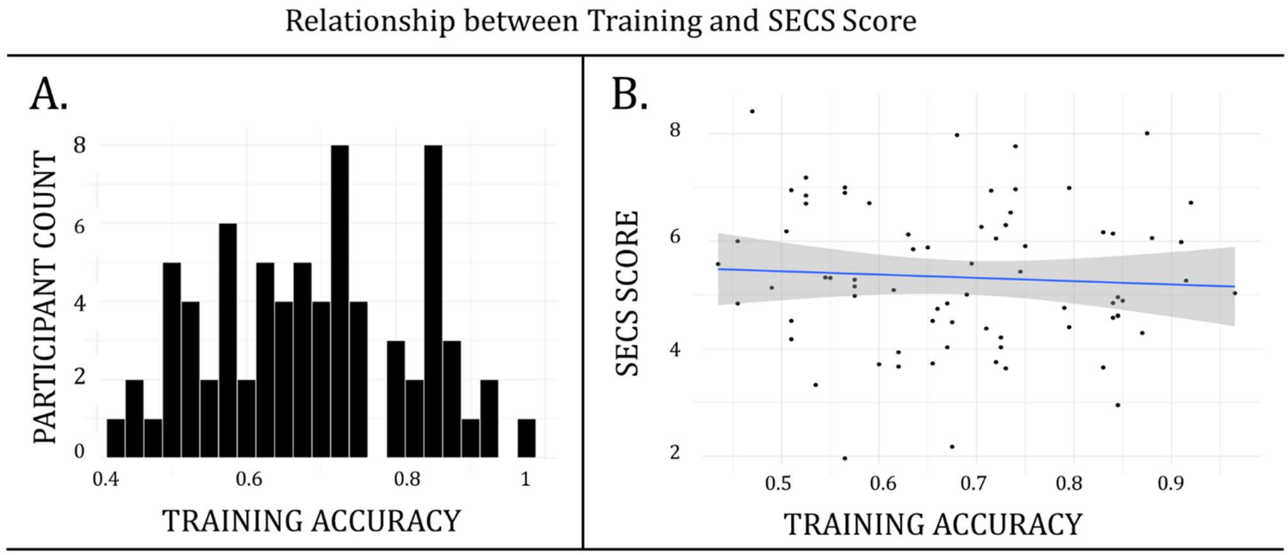
Statistical analyses were largely the same as in experiment 1. I computed the average training accuracy, average generalization performance, and corrected hit rate for each participant and used single sample t-tests to compare these metrics to chance levels.

Political Typology

SECS was calculated by taking the average of the participants' score for each individual topic and dividing that number by 10 to get a number that was between 0 – 10. Notably, two topics (*Abortion* and *Welfare Benefits)* on the SECS were reverse coded, meaning that the number that was averaged was subtracted by 100. This is because the more positive someone feels about abortion (i.e. pro-choice) the less conservative they are since the conservative position is pro-life. The SECS score was analyzed alongside participants' affiliation to ensure it was a valid measure.

Results

Figure 8



Note: A) Performance of Training task for Participants in Experiment 1. *B)* Correlation between Training Accuracy and Typology Score.

Training

While being trained on the exemplars, participants performed above chance ($M = 0.68$, $SD = 0.13$, $t(72) = 11.79$, $p < .001$; *Figure 9A*). This suggests that participants were able to learn the categories, similar to experiment 1 participants. When examining the relationship between training accuracy and participants' SECS score it appears that there is virtually no correlation ($t(71) = -0.52$, $r = -0.06$, $p = .608$; *Figure 9B*).

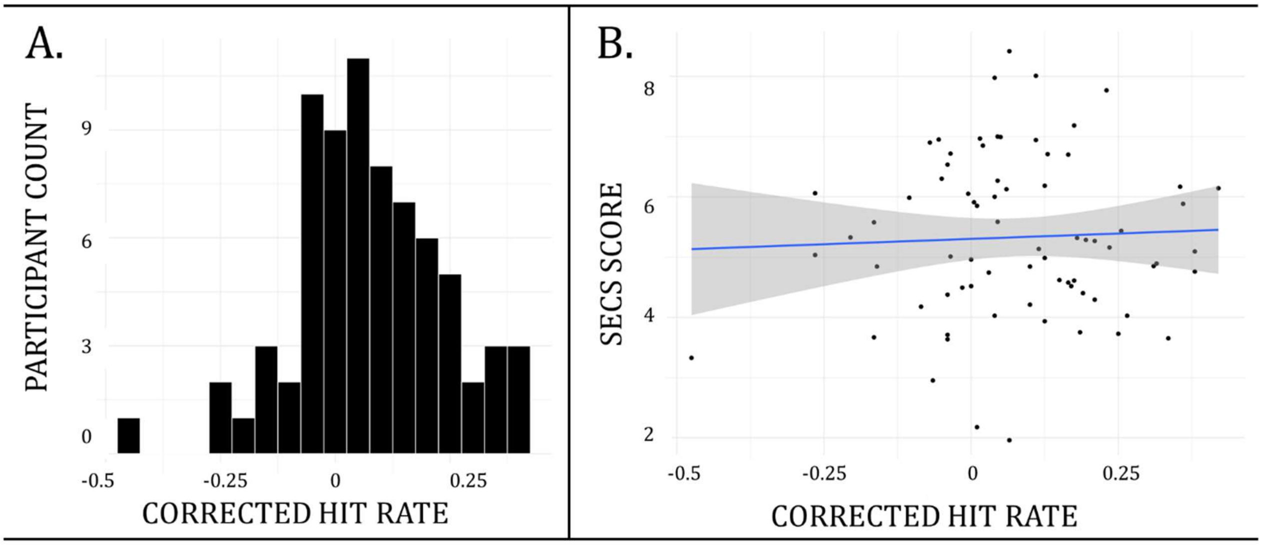
Recognition

When examining participants corrected hit rate, it ranged from -0.5 to 0.5, with a majority of participants scoring above chance ($M = 0.07$, $SD = 0.16$, $t(72) = 3.87$, $p < .001$; *Figure 10A*). Thus, overall, participants were moderately able to differentiate old stimuli from new stimuli. There proved to be no relationship between corrected hit rate and SECS score ($t(71) = 0.37$, $r =$

0.04, p = .711; *Figure 10B*)

Figure 9

Relationship between Recognition and SECS Score



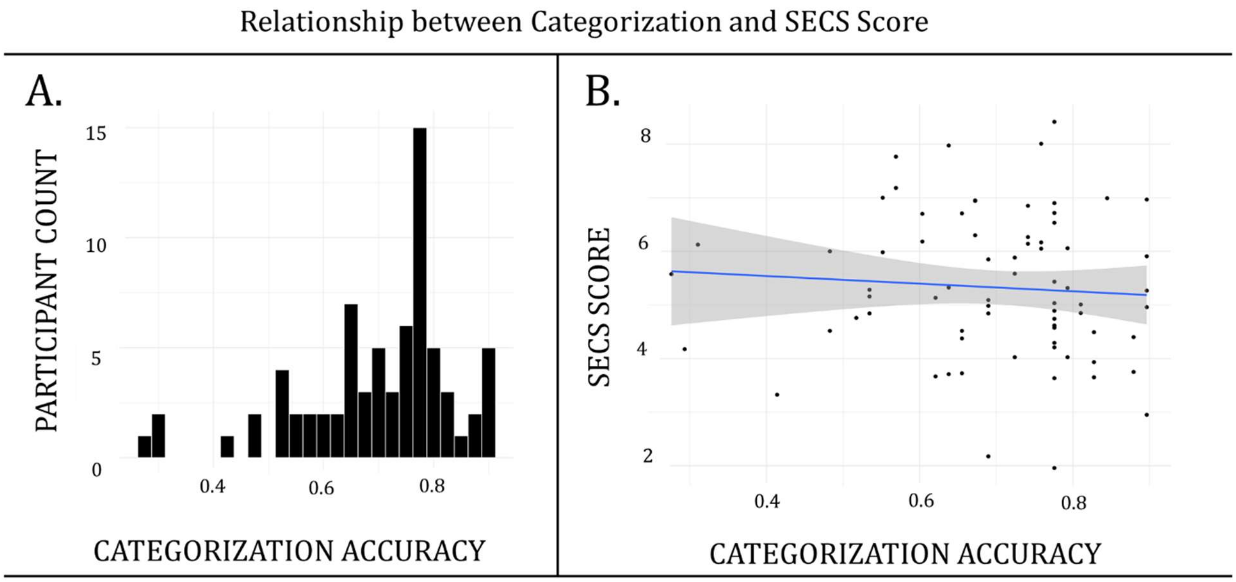
Note: A) Performance of Recognition task for Participants in Experiment 2. *B)* Correlation between Participants' SECS score and Corrected Hit Rate.

Generalization

Participants performed above chance during the categorization task, (M = 0.69, SD = 0.13, $t(72)$ = 12.12, p < .001; *Figure 11A*). This pattern suggests that participants were able to generalize prior knowledge to ne stimuli. Like the prior tasks, there was no relationship between

SECS score and accuracy ($t(71) = -0.62$, $r = -0.07$, $p = .533$; *Figure 11B*).

Figure 10

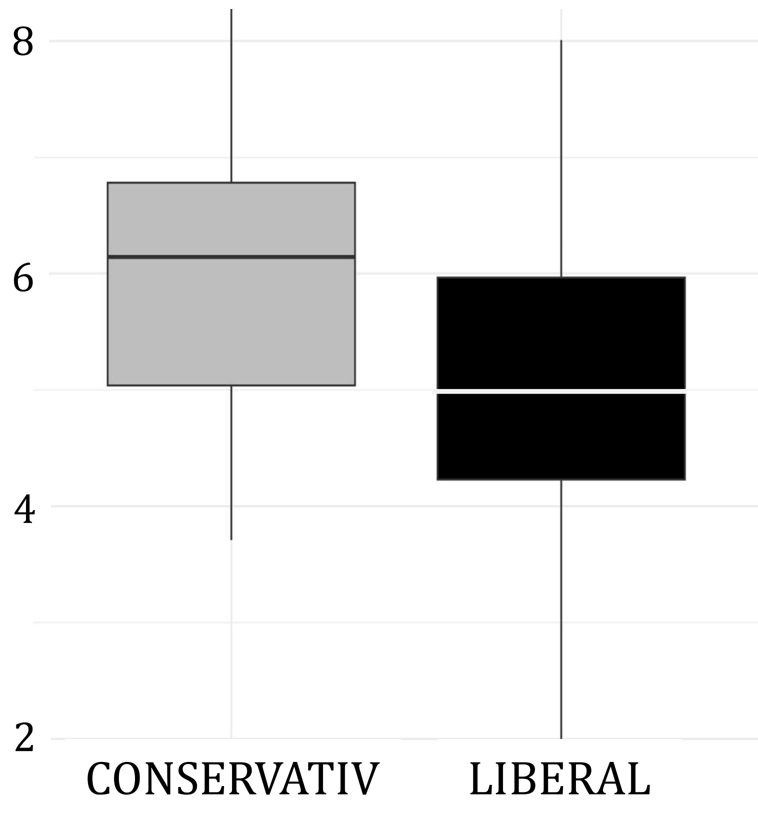


Note: A) Performance of Categorization task for Participants in Experiment 2. *B)* Correlation between Participants' SECS score and Categorization Accuracy.

SECS

To validate SECS, I compared the scores between self-identified liberals and self-identified conservatives. There was one participant who identified as independent, and per the instructions on how to analyze the SECS, we removed that one participant (Everett, 2013). Additionally, the SECS was able to differentiate conservatives from liberals, replicating what Everett found in his study utilizing the SECS score. When examining the efficacy of SECS, that is how accurately is it able to differentiate between conservatives and liberals, the SECS was effective (Mconservative = 6.01, Mliberal = 5.08, $t(71) = 2.69$, $p = 0.009$; *Figure 12*).

Figure 11 Relationship between SECS score and affiliation



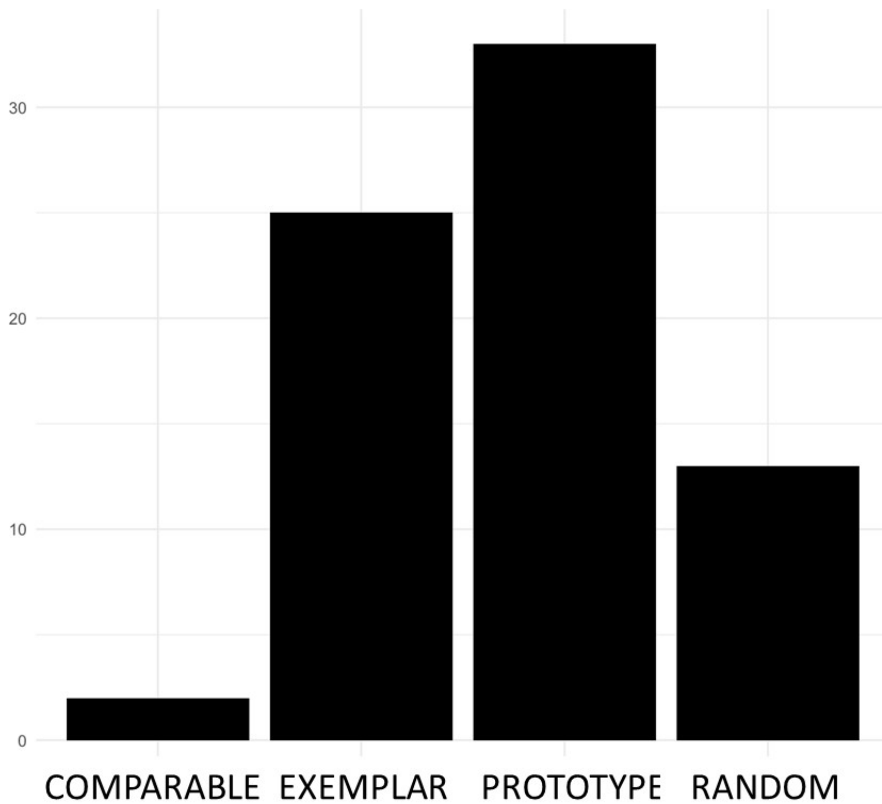
Note: Distribution of Final SECS score by affiliation. The box represents the middle 50% of the data. The bottom part of the box is the lower quartile, with the upper part of the box being the upper quartile. The line inside of the box represents the median number in the data. The whiskers represent the range of the data, with any dots being outliers.

SECS Score & Generalization Strategy

A majority of participants used the prototype categorization strategy, followed by the exemplar strategy (*Figure 13).* After validating SECS, we used it to determine if more conservative people (a higher score) correlate with a specific type of strategy. Like before, the participants who were either comparable or random categorization strategy were removed from the sample when analyzing categorization strategy with SECS score. It was found that the more conservative someone was the more likely they were to use a prototypist categorization strategy, consequently, the more liberal someone was the more likely they were to deploy an exemplarist categorization strategy ($t(55) = -2.04$, $p = .045$; *Figure 14*)

Figure 12

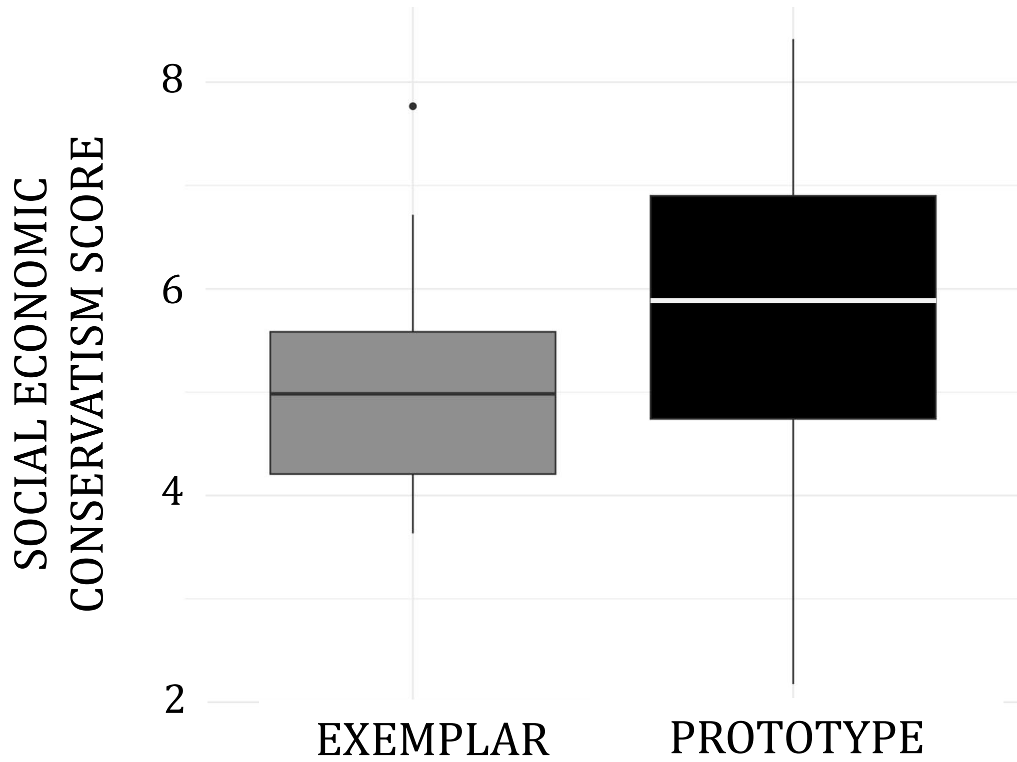
Bar Graph detailing strategies from Experiment 2



Note: Categorization strategies from Experiment 2.

Figure 13

Relationship between SECS score and Categorization Strategy



Note: Distribution of Final SECS score by Categorization Strategy

Discussion

Experiment 1's behavioral results (Training, Categorization and Recognition accuracy) were replicated in Experiment 2. Additionally, I found that SECS managed to correctly identify conservatives from liberals based on participants' final SECS score. Then by using this final SECS score, it was found that the more conservative a participant scored, the more likely they were to use a prototypical categorization strategy, whereas the more liberal they scored, the more likely they were to use an exemplarist strategy.

General Discussion

This thesis sought to expand the current understanding of the different cognitive styles of liberals and conservatives specifically their strategies for concept learning. We did this by administering a category learning task to 190 participants across two experiments. In both experiments, we did not find a relationship between overall performance and political typology, but in experiment 2, we altered the typology survey to the SECS score and found higher scores (meaning more conservative thought) correlated with a higher likelihood of using a prototype categorization strategy.

Prior Researchers found that conservatives tended to be swayed my smaller details which could mean that they were focusing on specific examples rather than the broad picture (Conway III et al., 2016). Given this, I hypothesized that that conservatives may be exemplar thinkers, whereas liberals would be prototype thinkers. The findings of this study went against this hypothesis, conservatives correlated with a higher rate of using the prototype categorization strategy. There could be a few reasons for this, but the main one I found is that prototype thinkers can also be carried away in decision making processes, as the internal prototypical representation may be used as a heuristic for what they are looking at (Seger & Peterson, 2013). Researchers have also found that conservatives are more likely to rely on their intuitive thinking skills, rather than reflective thinking, again aiding to them being more prototypical thinkers (Deppe et al., 2015). Additionally, when speculating about recent events, it appears that liberal anchors pointing towards specific policies and conservative anchors generalizing political actors with broad strokes of policies.

Despite not seeing any difference in cognitive performance, this was also an exciting result to see. With no correlation with typology score and cognitive performance, even in

Experiment 2, meant that political affiliation had no impact on performance at all. The ability for participants to learn the category structure was not affected by their typology, instead it was only the cognitive style that was different between the two affiliations.

Experiment 1 also suffered from a lack of conservatives due to the fact that the survey was not valid in properly determining political affiliations. Experiment 2 was run to rectify some of the existing issues, namely the Typology survey and the lack of conservative sample. Prior research in cognition's relation to political affiliation have suffered from several shortcomings. The first and foremost being the measure of political affiliation. Here, I used two separate measures, the Pew Political Typology Survey and the Social Economic Conservatism Scale. In Experiment 1, the Pew Typology Survey was not valid as it only identified 5 conservatives in a sample of 89 participants. Whereas in Experiment 2, using the Social Economic Conservatism Scale, which managed to properly place 20 conservatives in a total sample of 73 participants. Despite this, the sample is still not properly balanced in terms of gender, age, or political affiliations. Future research to balance the sample in conservatives and liberals will help validate this study further by properly showing the difference between the two political affiliations.

This thesis has direct ties to current real-world problems, namely the stark rise in polarization, which continuously drives Americans further apart. By understanding how the different political affiliation learns concepts, society can tailor the information to this understanding – developing an understanding of information to develop a shared reality between everyone. The results of this study are an important contribution to the academic field, as well as implications for the greater field of political science.

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