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Final Project Report

Introduction

In-group bias is the preferential treatment of people with whom you share a common identity, such as gender, race, or culture. In-group bias can be harmful when it leads to unfair outcomes, such as when a perfectly qualified job candidate is not hired because of their race. Current research is focused on reducing in-group bias to mitigate its harmful effects (Wang et al., 2015). This research team primarily focuses on social cognitive effects on neuroscience for in-group versus out-group members through different primings and visualizing brain activity and interactions in response to different stimuli. Other studies have also identified that promoting a positive and inclusive group and relations within that group is a way to mitigate in-group bias by focusing on how people are oriented in a social context or setting before their exposure to that setting (Bettencourt et al.,1997).

Along this line, we are investigating if in-group bias can be influenced by priming people with a learning versus performance orientation. A *learning orientation* is other-focused (trying to get to know another person), whereas a *performance orientation* is self-focused (trying to make a good impression). Other studies have demonstrated that in-group bias is influenced by the priming received, so we expect the priming our participants receive will affect their in-group bias (Bettencourt et al., 1997). Specifically, we will 1) determine how perspective-taking, empathetic concern, and altruism are different among in-group versus out-group members, 2) investigate more subtle language differences when addressing in-group versus out-group members, 3) determine if the priming received (learning versus performance) influenced perspective-taking, empathetic concern, and altruism towards strangers, and 4) examine patterns in survey responses by gender, a potentially important factor to consider when investigating in-group bias.

Data

This data was sourced from a study conducted by the Department of Psychology at Northwestern University. Participants were recruited through Amazon's Mechanical Turk (MTurk) and completed the survey on Qualtrics after providing informed consent. The study targeted white adults identifying as male or female. To ensure adherence to these demographic criteria, a pre-screening was conducted.

In this study, two independent variables were employed to investigate the impact of social orientation on in-group bias. The dataset consists of 124 participants with an average age of 34.61 years, following the removal of cases with missing data. Among these participants, 69 are females (55.65%), while 55 are males (44.35%).

Independent Variables

The first independent variable was *Learning/Performance Orientation.* Participants were randomly primed with a learning or performance orientation by reflecting on a time when they tried to get to know someone new or by reflecting on a time when they tried to get someone new to like them. After randomization, 39 females and 24 males were primed for the *Learning Orientation*, and 30 females and 31 males for the *Performance Orientation*. The second independent variable was *In-Group/Out-Group Stranger,* with 40 females and 25 males in the *In-Group* condition and 29 females and 30 males in the *Out-Group* condition. Participants were randomly assigned to read a first-person account from an in-group (white) or out-group (black) stranger who just went through a breakup.

Dependent Variables

Participants’ responses to the first person account they read constituted the dependent variables in this study. First participants wrote a 1-2 paragraph letter of support to the stranger whose account they read. We extracted the sentiments expressed in this letter and used this as a dependent variable called *Sentiment Expressed*. Then, *Perspective Taking* was measured using a five-item questionnaire that assessed how easily participants could adopt the perspective of the person they read about. Next, *Empathic Concern* was evaluated through a single-item scale designed to gauge the level of empathic concern or compassion that participants felt for the person they read about. Finally, *Altruism* was assessed via the Dictator Game where participants could give some, none, or all of their 25 cent compensation to the stranger they read about. This provided a measure of altruistic behavior by quantifying how much of their own resources, such as money, participants were willing to offer a stranger.

Covariates & Quality Assurance

In addition to the primary variables, several potential covariates were considered to control for extraneous factors that might influence the study's outcomes. These covariates included *Trait-Level Learning and Performance Orientation, Age,* and *Gender*. *Trait-Level Learning and Performance Orientation* were each assessed with an 8-item scale measuring participants' pre-existing trait-level inclination toward learning or performance orientation. People with a high performance orientation are likely to prefer completing tasks that they are already skilled at, and they don’t like making mistakes. In contrast, people with a high learning orientation are eager to take on challenges and to learn from mistakes. *Age* and *Gender* were both self-reported.

Quality checks were also implemented to ensure data reliability. For instance, an attention check was employed to confirm participants' engagement in the study by asking them to describe what they had read; those who did not answer this question were identified as potentially not earnestly taking the survey. Another attention check was included that asked participants to select a specific answer to prove they were carefully taking the survey. Additionally, participants were presented with an include or exclude quality check. In this assessment, participants had the opportunity to self-report the accuracy and thoroughness of their survey completion, ensuring data quality and the reliability of participant responses. All of these quality checks served to verify the quality of the data because survey data can sometimes be unreliable.

Data Cleaning Process

To clean and preprocess the data, we reformatted variable names, removed unused variables, reformatted some survey responses, and created new variables. We reformatted the variable names by removing capital letters and replacing spaces with underscores so they were easier to work with. Then, we removed the survey metadata that we weren't including in any of our analyses. Some of the survey responses were categorically encoded. For example, "male" was denoted with a 1 and "female" was denoted with a 2. Therefore, we unencoded the responses so we wouldn't have to repeatedly reference the survey documentation.

Next, we created columns indicating each participants' condition (in-group/out-group and priming received). Previously, there wasn't a single column indicating which condition participants were in. Rather, there were columns that only had data if a participant was within a certain condition. We need one column containing which condition a participant was in to facilitate analysis. Then, we had to clean up the free responses to the dictator game question. For some responses, there was additional text explaining their choice, and one person answered “125” when the maximum possible value was “25.” Therefore, we removed the additional text and assumed this was a typo, changing their answer to “25.”

Additionally, we calculated the average scores on scales with multiple items. Much of the survey data was interpreted as string when it was actually numeric data, so we had to convert some of the data types. This step was necessary prior to calculating average scores for scales with multiple items, including the *Perspective Taking* scale and the *Trait-Level Learning/Performance Orientation* scale. Three items in the *Perspective Taking* scale had to be reverse coded before the average score could be calculated. This was to create uniformity in the responses such that greater responses indicated someone was more skilled at perspective taking.

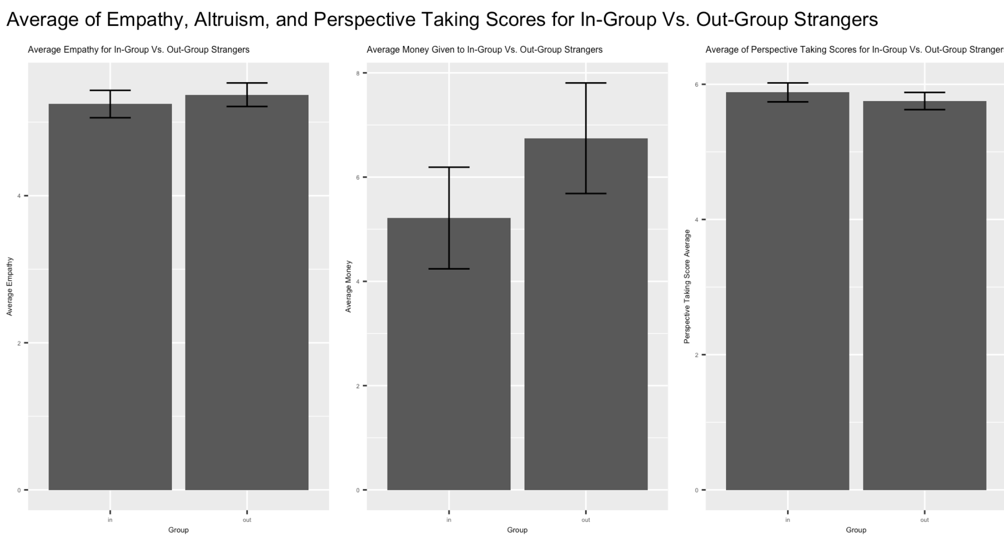
For example, this is a statement that had to be reverse coded: “I sometimes found it difficult to see things from the other participant's point of view.” Participants could answer on a scale from 1 to 7. Answering a 1 meant the participant felt the statement did not describe them at all, while answering a 7 meant the participant felt the statement described them extremely well. If someone felt this statement described them very well, then they were less skilled at perspective taking. However, for the other questions, a greater response represented more skilled perspective taking. Therefore, this question was reverse coded so that 7 became 1, 6 became 2, and so on. This ensured a participant was better at perspective taking if they had a greater average response to all of the perspective taking questions.

Next, we removed blank and mostly blank surveys, reviewed the quality checks, and removed additional responses if necessary. Blank surveys were introduced in the dataset by people who clicked on the survey link but didn't answer any questions. Furthermore, 92 out of 218 participants didn't answer any of the questions we used for analysis, so they had to be removed. Upon inspecting the age and gender of the removed participants, there was no obvious pattern to explain why these people did not complete the survey. There were also 2 participants who clearly did not honestly respond to the survey because their free responses were nonsensical or vulgar. They also gave the same response to every multiple choice question. Therefore, we were left with 124 participants. One of these participants didn't answer the last question on their trait-level learning orientation, so their blank response was replaced with the median response for that question.

Lastly, we performed textual analysis on the letters of support by determining word usage frequency, average sentiment expressed, and pronoun usage. To start, we separated each word from the participants' responses into a "token," essentially making each word its own observation. When determining word usage frequency, we made sure to remove any stop words, or words that had no sentiment associated with them such as "and," "you," and "too." After removing these words, we assigned all other words a "sentiment score" between 5 and -5 from the AFINN lexicon list, with 5 being the most positive and -5 being the most negative. After the scores were assigned, we calculated the average sentiment expressed for each specific participant and added this to our original data frame. There were 11 participants whose responses had no sentiment expressed. Lastly, we calculated pronoun usage for each participant. We counted the number of first, second, and third-person pronouns each participant used and added these counts to the data frame.

Exploratory Data Analysis

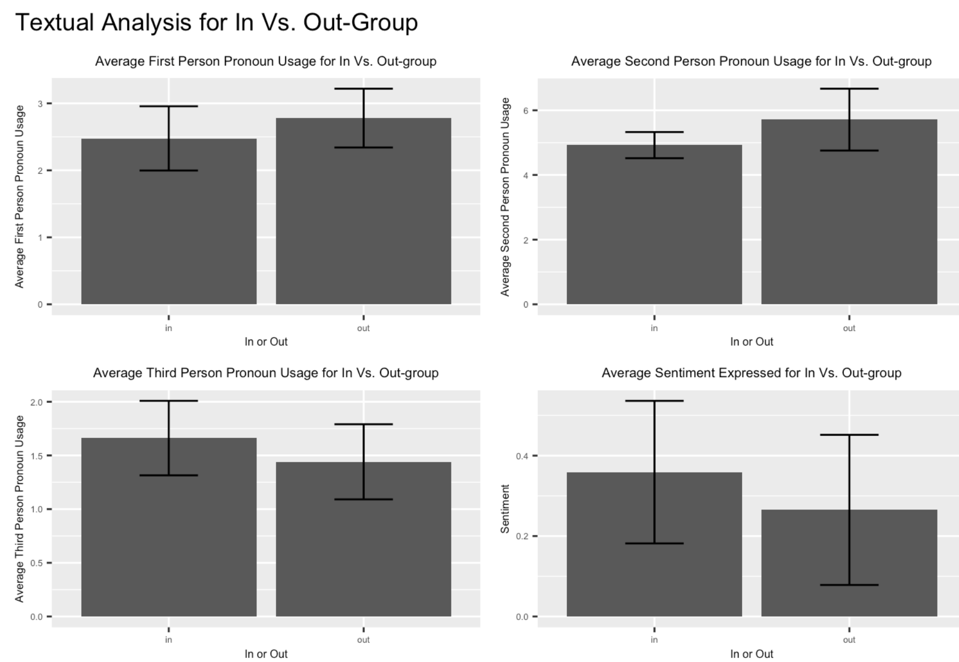
In-Group vs. Out-Group: Empathetic Concern, Altruism, and Perspective Taking



Graph 1: Average of Empathy, Altruism, and Perspective Taking Scores for In-Group Vs. Out-Group Strangers

We were primarily interested in determining the differential treatment of in-group versus out-group strangers, so we investigated participants' display of empathy, altruism, and understanding towards in-group and out-group strangers. Graph 1 above displays participants' self-rated empathetic concern for, average money out of 25 cents given to (proxy for altruism) and self-rated ease of perspective taking for in-group versus out-group strangers. Participants were able to rate their agreement with statements assessing empathetic concern and perspective taking on a scale from 1 (none) to 7 (an extreme amount). Originally, we thought we would be able to identify an individual's group affiliation (in-group or out-group) by analyzing their survey responses regarding altruism, empathy, and perspective taking. Upon conducting exploratory data analysis, we no longer believe this to be the case. Graph 1 supports the hypothesis that there is no significant difference in the empathy, altruism, and perspective taking towards in-group or out-group members since the error bars overlap. There is a chance that the reason we do not see a difference in empathy, altruism or perspective-taking for in and out groups is because of the way that participants were primed.

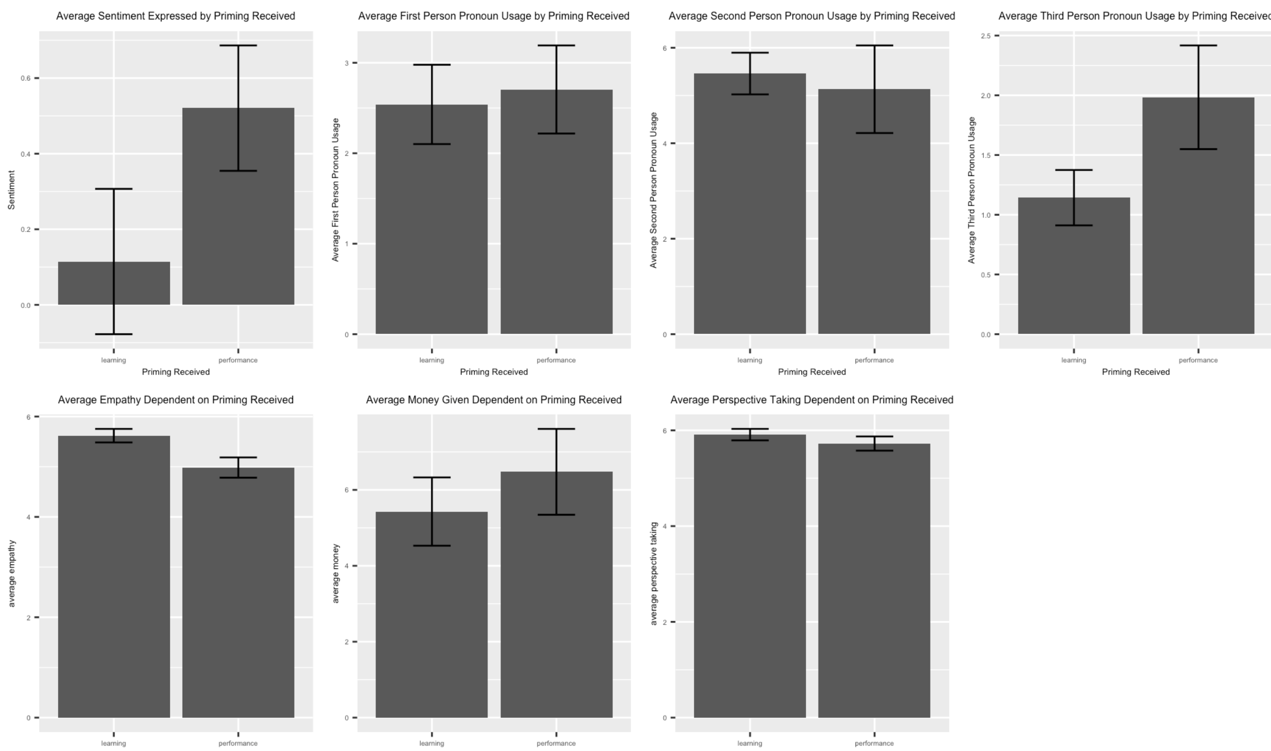
Textual Analysis for In-Group vs. Out-Group



Graph 2: Average First, Second, and Third Person Pronoun Usage and Average Sentiment Expressed for In Vs. Out-Group

Another dimension along which we believed the treatment of in-group and out-group members could differ was language usage. We thought that perhaps the differential treatment of in-group and out-group members could be more subtle, such as how participants' chose to communicate. Therefore, we explored language usage in letters of support to in-group versus out-group members. Graph 2 above displays participants' first, second, and third person pronoun usage along with the sentiment expressed by participants for the in-group and out-group members. As we can see in Graph 2, there does not appear to be any differences between pronoun usage and sentiment expressed for in- and out-groups because the error bars overlap. Building upon our first hypothesis, we hypothesize that we will not be able to differentiate which group someone was in using textual analysis. There may be a chance that we will be able to see differences when taking priming into consideration.

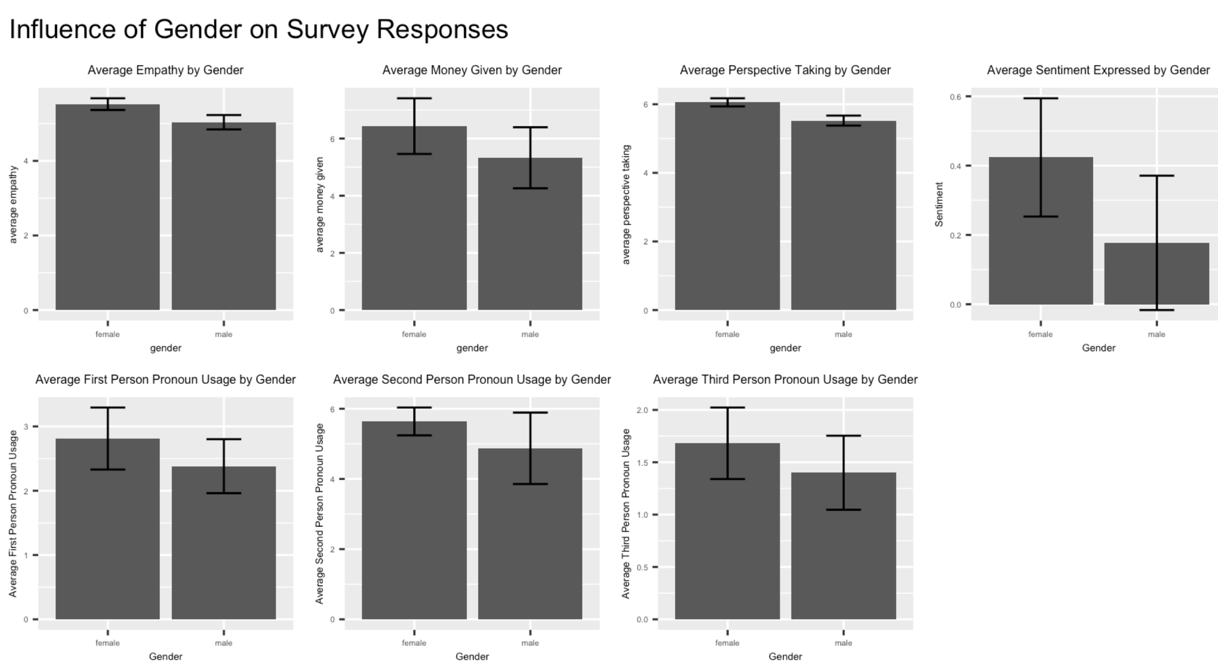
Influence of Priming on Survey Responses



Graph 3: Influence of priming on all survey responses, including empathy, money given, perspective-taking, sentiment, and pronoun usage

Next, we were interested if participants survey responses changed depending on which priming they received, and we initially thought we would see a difference in the survey responses dependent on the priming received. Upon further exploration in Graph 3 above, we discovered few significant differences in each survey response, except for sentiment,third person pronoun usage, and empathy. For average sentiment, we found that participants who underwent performance priming were inclined to incorporate a greater number of words with positive connotations in their support letters. For third person pronoun usage, we found that participants who received the performance priming were more inclined to use third person pronouns than participants who received the learning priming. Lastly, participants who received the learning priming expressed more empathy on average. All of these differences are likely to be significant since the error bars don’t overlap.Due to the differences in sentiment, third person pronoun usage, and empathy, we may be able to detect which priming a participant received, but there could be some other factors that should be taken into account to accurately predict the priming received.

Influence of Gender on Survey Responses



Graph 4: Influence of gender on all survey responses, including empathy, money given, perspective-taking, sentiment, and pronoun usage

Lastly, we were interested in seeing if a participants' gender had any affect on survey responses, and if a participants' gender could be speculated based on survey responses. The results in Graph 4 show that while there was a greater amount of average empathy, money given, perspective-taking, sentiment, and pronoun usage by females than by males, only some of these differences are likely to be significant. There are possibly significant differences in empathy and perspective taking, so these predictors could potentially be used by a model to discern someone's gender.We hypothesize that we may be able to predict a participants' gender based on survey responses, particularly empathy and perspective taking.

Hypotheses

Based on all the graphs above, these were the four hypotheses we settled on. First, we hypothesized that we would not be able to detect which group someone was in (in-group or out-group) based on their responses to the questions in the survey related to altruism, empathy, and perspective taking. Second, we predicted that we would not be able to detect which group someone was in by including additional predictors procured from textual analysis, such as sentiment expressed and pronoun usage from the letter of support. Third, we predicted we may be able to detect which priming someone received based on their survey responses, particularly those related to empathy, perspective taking, altruism, sentiment expressed and pronoun usage in the letter of support. Lastly, we predicted that we may be able to predict participants' gender based on their survey responses, particularly those related to empathy and perspective taking.

Modeling

To begin modeling our data, the first pivotal step was defining the problem. We determined that each of our hypotheses were classification tasks. For the first and second hypothesis, we were interested in classifying in-group and out-group members, for the third hypothesis we were interested in classifying the priming received, and for the last hypothesis we were interested in classifying participants' gender based on survey responses. We decided to use logistic regression for these classification tasks due to the interpretability of the model output. It was important for us to be able to understand what the differences led to people being classified as in-group or out-group, learning or performance priming, and male or female. Furthermore, regularization could be implemented to prevent overfitting, which was a particular concern of ours due to our small sample size. We also used the liblinear solver for logistic regression because it is ideal for small sample sizes too.

Prior to training the logistic regression model, we processed the categorical columns indicating I*n-Group/Out-Group*, *Priming Received*, and *Gender* by numerically representing the categories. For *In-Group/Out-Group* classification, "in" is represented as 0, while "out" is encoded as 1. Similarly, types of priming received are numerically encoded, with "performance" designated as 0 and "learning" as 1. In the gender classification task, "male" is assigned the numeric value 0, while "female" is represented by 1.

The next step was defining the predictors and outcomes for each of our 4 hypotheses. For the first hypothesis, we chose to include 7 predictors: responses to 5 questions about perspective taking, 1 question about altruism, and 1 question about empathy. It is common practice to average responses to multiple questions from a singular psychometric scale, such as the 5 questions from the perspective taking scale. However, we chose to forego this. Although the questions in each scale were designed to represent the same psychological constructs, the relationship between each question and the outcome could be different, necessitating different coefficients for each question. Therefore, we used the individual questions as features rather than averages. The outcome for this hypothesis was I*n-Group/Out-Group.* Our second hypothesis built upon the first hypothesis. We believed we could improve upon the performance of the first model by including additional predictors procured from textual analysis. Therefore, we included the previous 7 predictors in addition to average sentiment, first person pronoun usage, second person pronoun usage, and third person pronoun usage for the second model. The outcome was the same as the first hypothesis, I*n-Group/Out-Group.* The model for the third hypothesis included the same 11 predictors as the second model, but the outcome was *Priming Received.* The final model for hypothesis 4 included the same 11 predictors as model 2 and 3, but also included trait-level learning and performance orientation. Trait-level learning and performance orientation were not included to predict I*n-Group/Out-Group* or *Priming Received* because someone's traits should not be indicative of which group they were assigned to since traits are not easily influenced. Participants' traits could be related to their gender though. The outcome for model 4 was *Gender.*

After defining the predictors and outcomes for each hypothesis, we split our dataset into training and test sets to ensure model performance on unseen data. 30% of the data was reserved for testing rather than the standard 20% because of our small sample size. We needed to retain enough data for testing. Then we performed feature scaling using standardization.

Feature scaling is typically recommended for logistic regression, and this enables consistent interpretation across all variables.

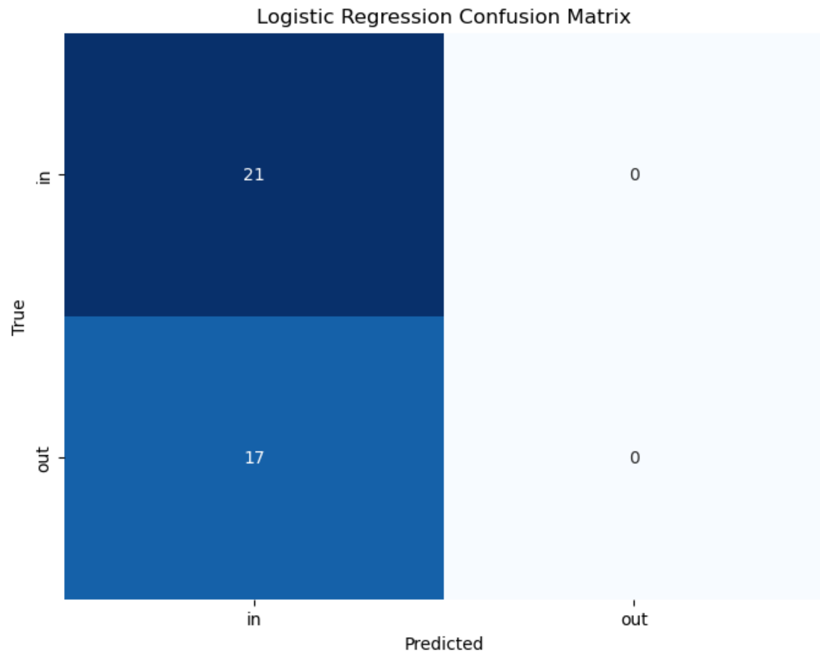
To optimize our model's performance, hyperparameter tuning was conducted using 5-fold cross-validation. We searched for the combination of regularization strength and regularization method that improved the model's accuracy the most. The regularization strength (C) could take on values of 0.001, 0.01, 0.1, 1, 10, or 100. Smaller values of C correspond to stronger regularization. The regularization method could be L1 or L2 regularization. We chose to use accuracy because we were not concerned about false positives or false negatives, and the class sizes were relatively balanced. We were mostly interested in the model's ability to accurately predict labels. It was ok if any of the models were slightly better at predicting one class over the other.

After completing hyperparameter tuning, we trained the model for each hypothesis and evaluated it on the test set. We looked at the classification report and confusion matrix for each model to understand each its strengths and weaknesses. Once again, accuracy was the most important metric for us because the class sizes were relatively balanced and we weren't concerned about false positives or negatives. Our final step was looking at the coefficients of the model to understand which features increased or decreased the odds of being part of the positive class. This helped us to understand what the differences were between each class, if any.

Discussion

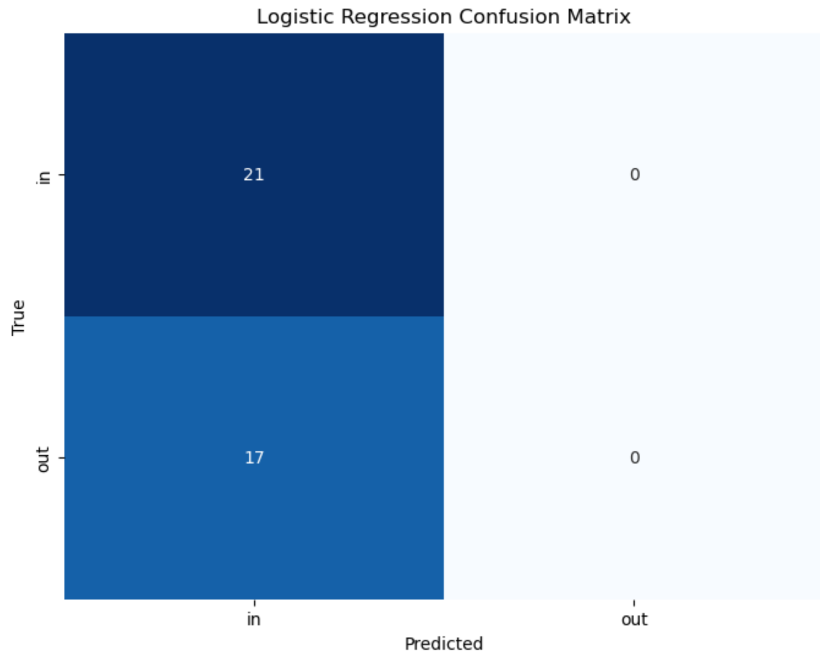
We aimed to understand how psychological concepts central to social interactions–empathy, altruism, perspective taking, and language usage–differed depending on group membership, social orientation, and gender. Our primary goal was to understand in-group bias better. How does group membership relate to individual psychology, thereby leading to the differential and potentially harmful treatment of out-group members. Our secondary goals included understanding how social orientation and gender influenced individual psychology because these factors could introduce complexity into how in-group bias is expressed. Accordingly, we had four distinct classification tasks: in-group vs. out-group, in-group vs. out-group with additional predictors, priming received, and gender. This section will discuss the outcomes of each model, critically assessing each predictor's weight and insights on the factors influencing social interactions, including group membership, social orientation, and gender. This examination explores the strengths and limitations of our models, guiding future investigations of in-group bias and social interactions in general.

The initial model's goal was to classify participants as in-group or out-group based solely on their responses to questions about perspective taking, empathy, and altruism. Unfortunately, the model's accuracy was only 55%, which you can see in the confusion matrix below. This aligned with our expectations from the exploratory data analysis. Notably, all coefficients were set to 0, which suggested that there was no discernible difference in how participants treated in-group vs out-group members on the basis of empathy, altruism, or perspective taking. This raises a critical question: could the inclusion of subtle language differences enhance the model's performance in capturing these distinctions? In the next paragraph, we explore the effects of linguistic nuances that may uncover hidden patterns that were absent in the initial model.



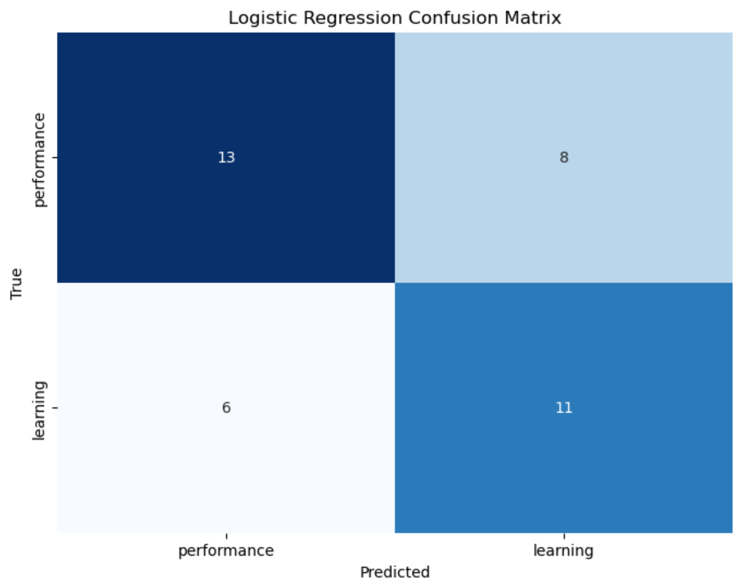
Confusion Matrix 1

To follow, the second modeling iteration incorporated additional parameters such as average sentiment and pronoun usage. Despite these changes, accuracy and all coefficients remained at 55% and 0, respectively, indicating persistent challenges in distinguishing between in-group and out-group behavioral patterns. The confusion matrix below represents the results of this model, which are identical to the previous model. These prompts triggered the need for a deeper investigation of the nature of these relationships: could more intricate linguistic features unlock patterns that more simple models seemingly fail to capture?



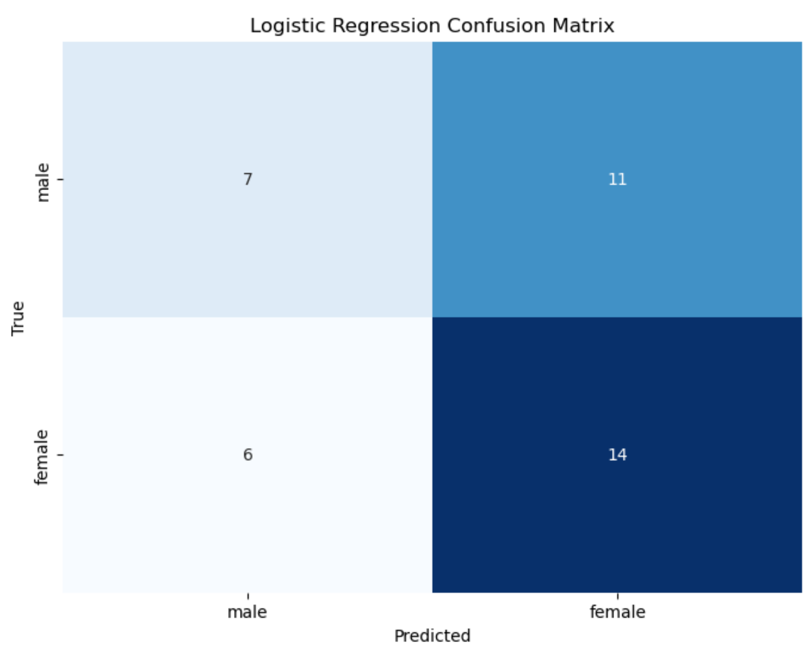
Confusion Matrix 2

The third model focused on predicting the type of priming received. This model achieved 63% accuracy, which is relatively higher accuracy than the first two models' 55% accuracies. The confusion matrix below depicts the results of this model. The model appears to be similarly capable of predicting whether someone received the learning or performance orientation since 61.9% of the performance and 64.7% of the learning primings were accurately predicted. The coefficients for these predictors were not set to 0, revealing potential nuances in participants' responses dependent on the priming they received. Interpretation of this model highlighted that higher empathy increased the likelihood of a participant being part of a learning group the most, while greater altruism decreased these odds. The betas that support each finding are 0.71 and -0.21, respectively. Additionally, pronoun usage played a role, suggesting that linguistic features can provide valuable insights into the experimental conditions. Participants that had higher usage of 1st and 3rd person pronouns in their letters of support decreased the odds of being part of the learning group, with betas of -0.23 and -0.44, respectively. In contrast, with a beta of 0.14, participants that tended to use 2nd person pronouns increased the odds of being part of the learning priming group. While this model proved a slight increase in performance over the former two, further experiments are still needed to validate these results and to make any generalizations since this study was exploratory. After this, we had one last question: can participants' survey responses be used to predict their gender?



Confusion Matrix 3

In the fourth and final model, we aimed to predict participants' gender and achieved an accuracy identical to models one and two: 55%. Unlike the previous models, the coefficients weren't set to 0, meaning that the predictors were at least somewhat meaningful, but caution is warranted in interpreting the coefficients since the performance of the model was so poor. When a participant indicated greater empathy, used more positively valence language, and disagreed with the statement "I sometimes found it difficult to see things from the other participant's point of view," this increased their odds of being female (betas = 0.23, 0.22, -0.29, respectively). The model's limited success underscores the complexity of gender prediction. Even if some of our variables were deemed as informative by our model (the coefficients weren't 0), there was a lack of consistency across the sample, hence the poor predictions of gender. Based on the confusion matrix below, it would appear that more males were falsely predicted to be females than the other way around. These are possibly males who expressed greater empathy, used more positively valenced language, and disagreed with the statement above. We can't make definite statements about how males and females vary on empathy, altruism, perspective taking, or language usage since the model performed so poorly. However, we can propose weak hypotheses, such as that females may express greater empathy, for further exploration.



Confusion Matrix 4

There were some important limitations and implications for our results. It's possible that our sample size was too small to detect any differences, that there were unrecorded features that could have distinguished in-group and out-group members, or that there truly were no differences in socialization between in-group and out-group members in our sample. Regardless of which explanation is correct, further exploration is necessary. If there truly were no differences in socialization between in-group and out-group members in our sample, then this would exemplify an aberration from previous research. It would be important to understand why there were no differences between in-group and out-group members in our sample. Even though in-group bias was not apparent in our sample, this does not mean it doesn't exist in other scenarios. It's possible that the priming received and gender of our participants influenced their responses, obscuring the differences that could have existed between in-group and out-group participants. Therefore, in-group bias is difficult to tease apart from other factors that may influence socialization, such as gender and social orientation.

Ethics

When discussing the ethical considerations for this project, we utilized the AREA Plus 4P Framework and chose three of the sixteen principles that we saw were best fit for this experiment. In conducting research on in-group bias, ethical considerations are paramount to ensure the integrity and fairness of the study. The AREA Plus (4p) Framework provides a comprehensive approach to addressing ethical concerns in research, and for this project, three key principles will be discussed: equality, diversity, and inclusion; potential conflicts; and unintended consequences.

Firstly, the principle of equality, diversity, and inclusion is fundamental in mitigating biases in research. The decision to enroll only white participants raises concerns about the generalizability and applicability of the study's findings to a broader population. To adhere to this principle, researchers should strive for diversity in their sample to capture a more representative picture of in-group bias. This involves considering a more inclusive participant pool, encompassing individuals from different racial and ethnic backgrounds, to enhance the external validity of the study.

The second principle, potential conflicts, underscores the importance of acknowledging and managing any conflicts of interest that may arise during the research process that are present with participants but in the researchers as well. If we are researching in-group bias, we are also subject to in-group bias. The opinions and ideas of people from broad cultural and ethnic backgrounds are incorporated into our research so that we don't unintentionally perpetuate any biases. In this context, the selection of exclusively white participants may introduce a potential conflict by perpetuating existing biases and reinforcing in-group dynamics. Researchers should transparently address these potential conflicts and take measures to minimize their impact, such as considering alternative sampling strategies that encompass a more diverse range of participants.

Unintended consequences, the third chosen principle, emphasizes the need to anticipate and address any unforeseen negative outcomes that may result from the research. In this study, the unintended consequence may be the reinforcement of stereotypes or the exclusion of perspectives from underrepresented groups, contributing to a perpetuation of in-group bias. Researchers should proactively assess these potential consequences and implement safeguards to mitigate harm, such as providing debriefing sessions that address any negative emotions or perceptions that may arise from the study.

To make the study more inclusive, researchers could have employed a more diverse recruitment strategy, ensuring the representation from individuals of different racial backgrounds. This would enhance the external validity of the study and contribute to a more nuanced understanding of in-group bias across diverse populations. Additionally, adopting a participatory research approach by involving individuals from different communities in the design and execution of the study could foster a more inclusive and culturally sensitive research environment.

Conclusion

Through a series of classification tasks, our study has provided valuable, tentative insights into the complexities of human interactions and relevant psychology. The inability to predict in-group/out-group membership based on empathy, altruism, perspective taking, and language usage suggests in-group bias did not exist within our sample, at least not on the dimensions investigated, or perhaps it was concealed by the priming participants received.

In our sample, other factors such as gender and priming received, rather than group membership, were more indicative of social dynamics. Notably, we achieved the highest accuracy when predicting the type of priming a participant received, with empathy emerging as the most influential predictor. This prompts speculation about the potential influence of learning orientation on empathy in our sample. If there was initially a difference in how much empathy participants felt toward in-group and out-group members, perhaps the learning priming was successful at reducing this difference. Although generalizations can't be made from our research due to its exploratory nature, the influence of a learning priming on empathy could be an interesting line of research for future researchers. Furthermore, although we were unable to predict gender with high accuracy, the influential predictors included ease of perspective-taking, empathy, and positively valenced language.

We can’t point to any consistent differences in the social dynamics between genders due to the low accuracy of the model, but these were the predictors that were picked out as being the most influential by the model. Therefore, it could be useful to investigate gender differences in perspective-taking, empathy, and positively valenced language further to see if this model was picking up on any slight differences that genuinely exist in society. However, there are many additional factors that shape a participant’s gender-based behavior that weren’t considered in this study, such as cultural differences, childhood traumatic events, societal norms, and early exposure to gender role expectations.

We must reemphasize the importance of ethics when conducting this study. This experiment further supports the necessity of equality, diversity, and inclusion to limit potential conflicts and unintended consequences of this project and future scientific analyses. We advocate for a more diverse participant pool, transparent acknowledgment of potential biases, and proactive consideration of unintended consequences. For example, we want to stress that even though in-group bias was not exhibited in our sample, this does not detract from an individual's personal experience or previous research which has demonstrated the harmful effects of in-group bias.

Overall, caution should be used when interpreting these results due to the exploratory nature of this project, the small sample size, the lack of cultural diversity among participants, and the potential threat of data quality issues. To draw more robust conclusions about social dynamics, future research efforts should embrace larger datasets, utilize more sophisticated linguistic analyses, and increase considerations of nuanced relationships. Ultimately, this study serves as a foundational step in research efforts, urging deeper investigations for a holistic understanding of the intricate interplay between psychological constructs and human behavior.

Acknowledgment

Team member	Contribution
Kaylee Billstone	**90**
Paulina Brown	**90**
Jaqueline Marroquin	**90**
Christiana Ozuna	**90**
Kirsten Richards	**90**
Kennedy Zapalac	**100**

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