CAUTION FATIGUE: GROUP IDENTIFICATION AND DISGUST PROVIDE PROTECTION IN THE COVID-19 PANDEMIC

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Abstract

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The current Coronavirus pandemic has yielded an abundance of concerns regarding the psychological effects of isolating a highly social species through widespread lockdowns and enhanced social distancing. Research show that many are suffering from mental health crises, while also refusing to isolate (Brooks et al., 2020; Czeiler, et al., 2020). These behaviors combine to increase risk of viral infection. An emerging term to explain this paradox is “Caution Fatigue”. Yet, there is no research that outlines its specific underlying mechanisms. The goal of this paper is to propose a series of models that delineate caution fatigue through the effects a) uncertainty b) the stereotype content model (Fiske et al., 2002) and c) group identification have on predicting the inhibition of risk perception through disgust. While caution fatigue is not ultimately observed, the conditions which one is willing to engage or mitigate risk are discussed. Unmasked faces are found to be viewed in a more negative affective state than masked faces which lends to increased feelings of group identification alongside uncertainty to promote feelings of disgust and risk. The findings presented here lack to perfectly encapsulate caution fatigue, but there is evidence of xenophobia against members of Asian heritage. Observations and implications are explained further.

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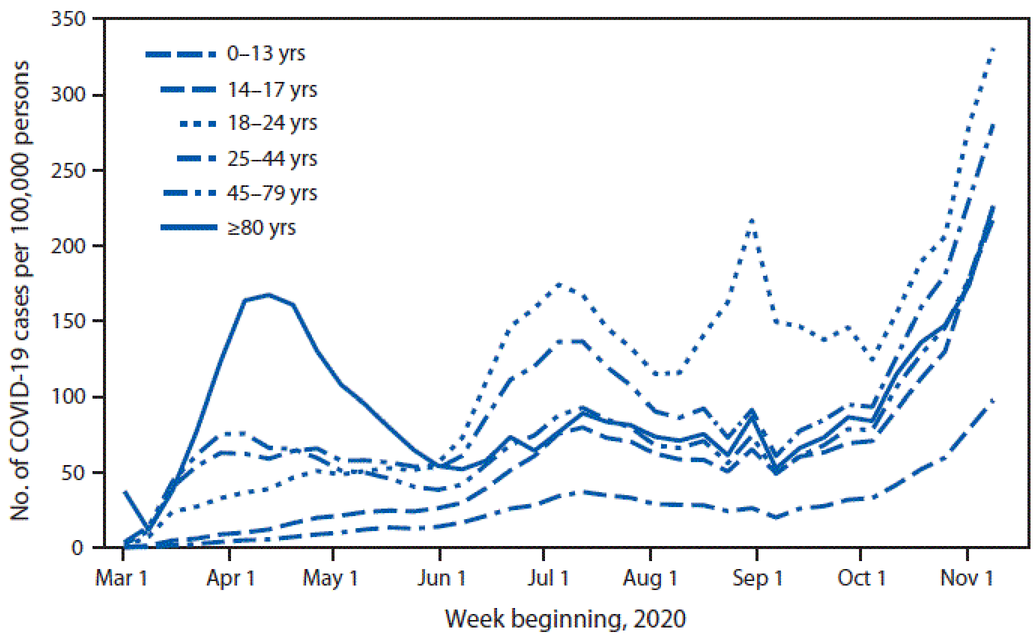
Introduction

The novel Coronavirus and the disease it produces (COVID-19) pose a real existential threat to those living through the pandemic. Vaccines are rolling out, but one-in-four Americans are refusing to prophylax while also failing to isolate (Brumfiel, 2021). A study conducted across 428 parents found that 37.7% of parents refuse to vaccinate both themselves and their children (Yigit, Ozkaya-Parlakay, & Senel, 2021). Paradoxically, data collected by the Center for Disease Control (CDC) in May show that the vast majority of United States (US) citizens believed in regulations aimed at reducing COVID-19 infection, but were less likely to participate in mitigating behaviors (Czeiler, et al., 2020). What more, 79.5% of the US supported business closures, 87.7% of the US believed in social distancing, and 82.4% thought groups should not gather. Considerably less people were actually self-isolating (77.3%), or keeping less than 6 feet from others (58.2%), and only 60.3% of the US reported to wear face coverings in public spaces (Czeiler, et al., 2020). Newer reports from November 1st of 2020 show a steady increase in viral transmission as shown in figure 1 (Duca, Xu, Price, McLean, 2021).

Moreover, a review of mental health data across 24 studies found that those experiencing this pandemic had an increase in feelings of stress, frustration, and even boredom (Brooks et al., 2020). Feelings of distress were tied to ambiguity of the future and resources available. Lastly, there was an increased awareness of isolation leading to a fear of diminished social standing among peers. The first study presents a dissonance between understanding what helps mitigate infection and actually engaging in the behavior, and the latter two show mental health declining. As a result of this evidence, citizens are putting themselves and others at risk for viral infection. It is imperative that current research is aimed to understand what processes underlie risk-taking behaviors so that solutions can be found.

Figure 1

Graph showing cases increasing from March to November. Each line represents a different age range as per legend (Ceizler, et al., 2020).



Recently, the media and a small group of clinical psychologists have argued that caution fatigue is at work for the aforementioned transmission spikes. Unfortunately, this term is rooted in client observation and lacks empirical evidence that explains the mechanisms under which this fatigue is brought on and carried. Cruwys and colleagues (2020) propose decreased risk perception is in some way influenced by disgust and trust, but the process is not entirely known. The goal of the present paper is to propose a testable model of caution fatigue that is rooted in research. Largely, I believe that caution fatigue is the willingness to engage in risk through minimizing the threat one may be enduring. The source of this behavior is mainly contingent on intergroup social cognitions. Constituents of this cognition relies on two forces. The first is how self-uncertainty influences adherence to group norms as well as how facial processing during the pandemic may increase uncertainty. The second is the reliance of stereotype heuristics for both in and out group members. These two sources, in turn, alter the behavioral immune system to undervalue pathogenic risk.

Affective Processing of Uncertainty Increases Congregation

Affect is often characterized by Russell and Barrett's (1999) definition as a mental state composed of two sources: valence and arousal. Valence being the binary spectrum of positive to negative while arousal is commonly aligned as the light switch (on or off). This model was expanded to illustrate the steps in which affect is experienced. The Modal Model states that a situation arises which in turn must be attended to and appraised (Gross, 2014). The appraisal of said events lead to an emotional response. This fits into the original concept of valence and arousal. The goal of any emotional response is regulation, especially in the realm of negative affect.

A common negatively associated affective experience is uncertainty. As stated above, uncertainty was a huge driving force for those surveyed in the pandemic (Brooks et al., 2020). While there is an abundance of positively valenced uncertainty, it is often linked to negative emotions as a protective factor against ambiguous outcomes in the environment (Anderson, Carleton, Diefenbach, and Han, 2019). Moreover, uncertainty is a fundamental aspect of life regardless of if it is perceived as such. Hirsch and colleagues (2012) posit the Entropy of Uncertainty model which explains the necessity of uncertainty. They argue that uncertainty is an adaptive mechanism acquired to overcome challenges in the environment by comparing what is present in one's surroundings and predicting how that may change. Additionally, the direction of uncertainty's valence and arousal can be mediated by goals and belief systems within groups, or the individual's subjective mood state. This often leads to uncertainty being experienced negatively because it represents one's inability to control or know the environment they inhabit. The novel coronavirus stands best as a motivating force for uncertainty. As posited in Hirsch's model, group membership is a mediating factor in decreasing uncertainty. When experiencing uncertainty, others wish to congregate. In the scope of COVID-19, congregating directly leads to viral infection.

Under the uncertainty-identity theory (Hogg, 2010; Hogg, 2013; Gaffney & Hogg, 2017; Gaffney, Rast, & Hogg, 2018), people can turn to group identification with self-relevant groups when feeling uncertain. Groups are important because they inform prescriptive norms which can reduce uncertainty. Group norms prescribe thoughts, feelings, and behvaiors, which people can use to tell then who they are and who they are not (Hogg, 2007; 2016). Participants who experience uncertainty tend to engage more regularly with group norms than those low in uncertainty. Contact with uncertainty also leads to increased identification with groups that are highly entitative (Hogg, Sherman, Dierselhuis, Maitner, & Moffitt, 2007). Entitative groups are perceived as more reliable because of their inherent structure and unequivocal norms. As uncertainty is exceptionally high within the COVID-19 pandemic, groups norms may decide choices regarding prophylaxis. For example, groups that are noticeably anti-masking may incur fellow compatriots to engage in similar behaviors through a wish to blend in with the group.

Research conducted during this pandemic has shown apparent risk-taking behavior being related to partisan group identification which may be because of uncertainty. Over 1 million survey respondents weighted by population found the strongest predictor for engaging in COVID-19-risk was partisan identity. Republicans over Democrats were more willing to break social distancing measures as time passed (Clinton, Cohen, Lapinksi, & Trussler, 2021). What more, Uncast-provided geo tracking of over 3,000 counties revealed that Republican-majority counties were 14% more likely to break social distancing measures by aggregating outside of households and visiting non-essential places of business than Democrat majority counties (Gollwitzer et al., 2020). It would appear here that identification with the Democratic party dictates group norms of isolation whereas identification with the Republican party is associated with norms that inclue breaking isolation. These trends increased during the sampling window. These observations were also related to increased infection rates as well as fatality growth. The present data suggests that this pandemic is perceived as a political issue and not a public health issue. In particular, this study showed that conservative identity is tied to more risk. In the context of uncertainty-identity theory, it is possible that Republicans are engaging in more risk because of uncertainty increasing group identification. Republicans are self-viewed as more entitative and exclusive, whereas

Democrats view themselves as more inclusive and similar to outgroup members (Christian, Nayyar, Riggio, & Abrams, 2018). Because Republican leaders prescribe norms of COVID-minimizing behaviors, members who experience uncertainty at all would potentially follow suit.

Uncertainty also increases risk perception through the processing of faces in their entirety. Somerville and colleagues (2004) found that higher anxiety states from uncertain events were associated with a greater signal increase for processing affectively-neutral faces in the right ventral amygdala which is recently ascribed as being involved in the rapid processing of fearful faces (Framorando et al., 2021). Lower state anxiety was also associated with lower signal increases with little to no difference between neutral and happy faces (Somerville et al., 2004). The uncertain group perceived neutral and negative faces more threateningly compared to the certainty group. COVID-19 is unique in that faces are covered to protect one another, but whole face processing is integral to risk evaluation (Leopold & Rhodes, 2010). Potentially, risk perception is becoming ineffective by masked faces which would cause others to defer to social groupings and norms. Blassi and colleagues (2009) contend that the amygdala acts preferentially to appraise neutral faces negatively when social judgement is added in as a factor. Without social context, happy faces were found to be approachable and negative faces as unapproachable. Neutral faces were non-significant between approachable or not. That is, until social judgment was factored in. This fMRI study found that fear of social judgement caused the amygdala to often defer to negativity. This could have inferences to social groupings such as the fear of pariahism by ingroups when engaging with outgroups. Therefore, uncertainty processing can be helped or hindered by social conditions which may extend to risk perception. Uncertainty-identity theory posits that groups would congregate when uncertain, however, facial processing literature states a deferral of negativity in ambiguous (i.e. masked) face settings. COVID-19 is unique in that faces are covered which can promote uncertainty, but also the uncertainty experienced during the pandemic (Brooks et al., 2020) may cause others to congregate.

Stereotype Content Model Increases Feelings of Safety Among Ingroups

Shared group membership leads to an undervaluing of risk which increases risk-taking, especially when the risk is most apparent with the in-group (Cruwys et al., 2021). The stereotype content model (SCM) posits that the social perception of both individuals and groups are contingent on stereotypes, which are organized along the dimensions of warmth and competence (Cuddy, Fiske, & Glick, 2008). First, warmth is necessary to appraise outgroups to evaluate what threat is posed to the group (Fiske, 2018). Competence is equally important to see the agentic nature of outgroups to provide harm or benefit to the group. The underlying principle of this duo-dimension theory is that warmth and competence are adaptively basic to be universal. This theme is consistent with a large body of classical social research regarding communion and agency through cognitive appraisals of behaviors geared to the group. An important factor in the SCM is emotions through processing warmth and competence which dictate patterns of biases propelling stereotype beliefs.

In the context of the COVID-19 pandemic, much more research is needed to know how social cognition has been impacted. Masks stand as a novel obstacle in group processing. There are differential warmth and competence ratings of masked faces. Masked faces are viewed as more trustworthy than unmasked faces (even more so than neutral or happy faces) with people willing to stand in closer proximity to masked individuals than unmasked individuals (Cartaud, Quesque, & Coello, 2021). However, no published paper has yet tested the effects group identification may have on this observed effect. It is entirely possible that unmasked faces of shared group membership would be seen as more warm than unmasked faces of outgroup members. The same would hold for competence as well.

The Behavioral Immune System is Prone to Failure

Lastly, risk perception during this pandemic may be motivated by disgust through the behavioral immune system (BIS). The BIS stands as the behaviors an organism engages in to guard itself against pathogenic infection (Schaller & Park, 2011). Disgust is a factor of this system as an evolutionary adaptive mechanism to promote avoidance. There are three mechanisms that engage this system. The first is the attenuation of immediate risks in the environment cuing infectious pathogens. The second mechanism triggers affective and cognitive responses to a perceived risk. Finally, the third is to act in a behavioral avoidance of such risk. For example, seeing a person not wearing a mask triggers the BIS to avoid said person and react out of disgust.

The BIS, is mostly researched in the realm of social cognition, but it also is linked to actual biological immune systems. The exact mechanisms that underlie this adaptive immune system is still unknown, but data shows a cyclic relationship between the two systems. For example, Miller and Maner (2011) found participants who had recently overcome an illness were more likely to engage in avoidant behaviors when seeing a "disfigured" individual than those who were not recently sick. However, these results are a weaker correlational example of the two-system's interconnectedness. Another experiment found that engagement of the behavioral immune system through a disgust induction was associated with a salivary inflammation response of the cytokine TNF-alpha (Stevenson et al., 2011). TNF-alpha is regularly secreted with albumin indicating increased vascular permeability which increases white blood cells present at the site for pathogenic management.

An important note of the BIS is that it is hypersensitive and prone to a high level of false positives. Faulkner and colleagues (2004) showed increased xenophobic attitudes and disgust by the perceiver was associated with immigrants of a different ethnic heritage than immigrants of shared heritage. Hypersensitivity towards outgroups also act inversely to perceptions of ingroup members (Khazie & Khan, 2019). Participants felt more disgust and had an increase in health risk perceptions in large crowds of outgroups than of ingroups. When participants were to imagine spending time in a large crowd of people, whether for a festival or rally of a contraidentified groups, they were more sensitive to disgust measures and perceived higher health risk with the outgroups. Whereas there was little to no health risk perceived in the same gatherings of ingroups. This suggests disproportionate health concerns when the risk is among those of shared group membership. This explains greatly the increased transmission spikes of COVID-19. Individuals are not processing pathogenic risk because they share group membership with those who are passing the viral illness on.

Overview of the Research

Research in part shows three things. (1) People will undervalue pathogenic risk when the host is from groups at which membership is shared. (2) Those experiencing higher levels of uncertainty will congregate with in group members to decrease uncertainty than those who are low in uncertainty, but also perceive ambiguous faces more negatively, and (3) Primed uncertainty will cause participants to perceive negative affect in neutral faces. What is not known is how these all function together to increase risk-taking behaviors. Additionally, no research has yet shown the extent to which group identification will impact perceived emotion of masked and unmasked faces. While uncertainty does increase group identification and normative behaviors, no research has tested the effect community safety has affected perceptions of COVID-19. These observations may work jointly to promote ineffectiveness in one's behavioral immune system leading to increased COVID-19 transmission.

Predictions

First, I predict that those high in uncertainty will perceive faces as more negatively, which in turn, will increase risk perception. Whereas those low in uncertainty will perceive faces as more positive leading to lowered risk perception which will be consistent with findings of uncertainty-identity theory. Secondly, group identification will positively affect warmth and competence of masked faces, which in turn, will negatively predict risk perception. Third, there will also be partisan differences between disgust of masked and unmasked faces because political membership is associated with risk perception. This will also extend to dimensions of warmth and competence, though denigration is possible as there are partisan differences observed in COVID-19 compliancy. Additionally, there will be partisan differences observed in COVID beliefs as well as emotion measurements of unmasked to masked faces.

Methods

This study was a survey-based experiment with multiple manipulations that included uncertainty and group identification. Measures of risk, disgust, perceived affect, and beliefs surrounding the pandemic have been collected as well. The survey was generated via Qualtrics, paid website with an accessible interface and strong security control. All testing was within accordance and acceptance of the Humboldt State University Institutional Review Board (IRB-20-130; 3/18/2021).

Participants

Participants were recruited from Amazon Mechanical Turk (MTURK). This sample included 400 participants across the United States, but only 244 were viable to be used for our results. The mean age was 34.66(*SD* = 11.63). The majority of the sample was white (100), while the second largest majority was Asian Indian (89). The third largest was black (23), and the remaining was Asian or Native Hawaiian. Party affiliation was largely Democrat (106), then Republican (64), followed by Independent (48), no party affiliation (23), and green (3) respectively. On the liberal to conservative binary, most participants were self-identified liberal (166) with the remaining (78) being conservative. Further demographic breakdowns can be found in the Appendix

An a priori power analysis of the moderated mediation yielded the need for 200 participants with power at .80. Moderated mediations typically require a large sample size and stands as the best design to choose for power. The power analysis was structured such that there was a moderate positive standardized relationship between uncertainty and mood congruency (ß = .40). Uncertainty as a moderating variable was also added as a moderate positive relationship between the predictor (ß = .40), the mediator (ß = .40), and a moderate positive relationship with the dependent variable (ß = .40). Lastly, perceived affect had a moderate negative relationship to risk perception (ß = .40). Power analysis computation was completed in RStudio using the “PWR2PPL” package (Aberson, 2021). Power was estimated with joint significance testing and 1,000 resampling method.

Measurements

Social/COVID-19 Perceptions.

These two scales are adapted from the CDC’s morbidity reports from the beginning of the COVID-19 pandemic (Czeiler, et al., 2020). The Social Perceptions scale includes 8 items detailing how well the test-taker believes their community is complying with COVID-19-safe behaviors. There are also items regarding how seriously their community is taking COVID-19 as an illness. The COVID-19 perceptions scale asks similar questions but framed to the individual answering, not the community. I have added items asking the extent to which the participant has traveled in the past few months, and if they have or will be receiving the COVID-19 vaccine.

Uncertainty scale.

The uncertainty scale is a five-item questionnaire from Grant and Hogg (2012) which asks respondents the degrees to which they feel confident in themselves and their future. There are also items asking about the certainty of America’s future.

Group identification.

The group identification scale is adapted from Hogg and Hardie (1991) and measures the level which participants identify with their group. For the scope of this project, the groups were either liberal or conservative identities.

Stereotype Content.

This scale is taken from Fiske and colleagues' (2002) original paper detailing the stereotype content model. This scale persists as an efficacious mode to testing the theory and includes eight items. Four of the items measure warmth while the remaining four measure competence. The scale items were totaled to reflect a general affect towards the given face.

Perceived Vulnerability to Disease.

The perceived vulnerability to disease (PVD) scale is a 15 item psychometrically-sound measure of disgust (Diaz, Soriano, & Belena, 2016). Items ask the test taker the amount they agree with behaviors intended to engage the behavioral immune system.

Risk Perception.

This scale is taken from a study measuring student attitudes surrounding COVID-19 in Wuhan at the beginning of their quarantine (Ding et al., 2020). The scale is four items measuring how salient the quarant's individual risk to COVID-19 is to them.

Affective Stimuli

Neutral Masked/Unmasked Faces.

Eight faces matched on sex and ethnicity were collected from the Racially Diverse Affective Expression (RADIATE) stimulus face bank (Tottenham et al., 2009;

Conley et al., 2018). This is a racially diverse set of faces standardized on emotion and image quality for research purposes. The face ethnicities include Asian, white, black, and Hispanic. Masks were added onto each face using the GNU Image Manipulation Photo editor (GIMP). Half of the faces were masked and half of the faces were unmasked. The masked condition included a typical white medical mask added to cover the nose and mouth. The unmasked condition included a mask added underneath the nose covering only the mouth. There will be two masked female faces, two unmasked female faces, two masked male faces, and two unmasked male faces. The faces can be seen in Appendix A.

Uncertainty Prime.

The uncertainty prime is adapted from established social identity theory work completed by Gaffney and colleagues (2014). This study is unique in that the primes have three conditions: certain, uncertain, and neutral. It is not common for this field to include a neutral condition. The uncertainty prime focuses on fictitious observations that the pandemic is nowhere near ending and that legislative regulations will have to continue for potentially years to come. Participants will have to write ways in which their life has been changed forever and is now uncertain going forward. The low uncertainty prime focuses on the opposite in that the pandemic is nearing its end with successful vaccinations. The respondents will write how the pandemic has changed their life for the better and they are certain moving forward. Lastly, the neutral condition just asks participants to write three things in their environment.

Procedure

MTURK workers signed up for this study were provided a Qualtrics link to the experiment. With the completion of informed consent, participants answered basic demographic questions then provided their perceptions about how seriously their community is taking COVID-19. Following, participants underwent one of three certainty primes as detailed above. The completion of the prime continued directly to measure their uncertainty levels. Group identification was then measured. Next, the participant was prompted to evaluate every preceding face making sure to memorize attributes of each face so that their recall can be measured. Every participant saw eight faces presented in random order. However, two unmasked faces were followed with the Perceived Vulnerability to Disease scale. Every face also has a series of items asking them to remember a random attribute, what mood the face appeared to be in, and the stereotype content model scale. The face section concluded with items asking risk perception and their personal beliefs regarding COVID-19. Every participant was then debriefed and compensated for their time.

Results

All data were analyzed using RStudio on Mac and is stored on author's personal computer and Qualtrics cloud.

Data Integrity

The data were first analyzed for its integrity through prime engagement, time spent taking the survey, and normalcy.

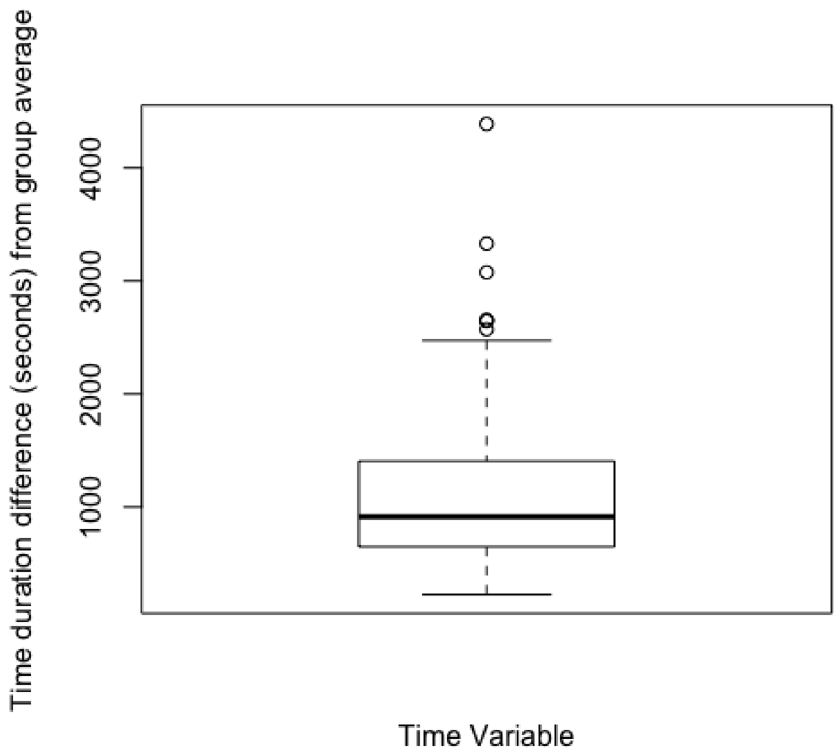
Integrity in the Sample.

There are mounting concerns regarding the legitimacy of using Amazon Mechanical Turk to collect samples (Chmielewski & Kucker, 2020). In an attempt to increase the validity of this tool, we have implemented attention checks that provide clear criteria for exclusion. The first criteria for exclusion included reviewing participant answers to the uncertainty prime. Cases were listwise deleted if they provided evidence of not fulfilling the prime's requirements. For some cases, this included copying and pasting the prime prompt into the text box. Other cases would paste online articles in the text box evidenced by responses that included: "If you would like to know about our policy regarding cookies please click learn more." This exclusion criteria reduced our sample size from 400 to 249.

The second attention included measuring time spent taking the survey. The mean time in seconds for participation was 1096.15 with a standard deviation of 615.17. After graphing a boxplot of the timing variable, no participants were shown to be outliers under the mean as seen in figure 2. Participants above the mean were still included in analysis because exclusion of such undermines individual differences in reading or response speeds. However, those under the mean would be multiple standard deviations below which is considerably fast for human response times. Lastly, incomplete cases were excluded to forego any ambiguity between incomplete cases that were due to attrition or faulty test-taking. The final sample size included 244 participants.

Figure 2

Boxplot of the timing variable. Scores above the box indicate outliers that are multiple standard deviations above the mean (1096.156 seconds).



Data Normalcy.

To meet the fundamental assumption of data normalcy among most statistical tests, predictor variables were evaluated for skew and kurtosis under a 99% confidence interval. Should the variable be non-normal, transformations were computed that included a square root, log linear, and inverse transformation. The best fix was chosen for each analysis. Each respective variable's estimate and transformation can be seen in Table 1.

Table 1

Skew and Kurtosis estimates are provided in 99% confidence intervals. Italicized variables are the chosen transformation. Variables without transformations are normally distributed and do not require investigation.

Variable	Skew	Kurtosis
Uncertainty	0.74(0.36, 1.15)	1.05(0.22, 2.14)
Uncertainty Square Root	*0.13(-0.39, 0.58)*	*0.91(0.18, 1.68)*
Uncertainty Log linear	-0.62(-1.22, -0.01)	1.97(0.61, 3.49)
Uncertainty Inverse	2.55(1.76, 3.26)	9.89(5.79, 15.76)
Community Belief	*0.26(-0.13, 0.80)*	*0.37(-0.24, 1.50)*
Group ID	0.84(0.25, 1.45)	2.36(1.09, 4.59)
Group ID Square root	*0.37(-0.38, 0.98)*	*1.91(0.94, 3.54)*
Group ID Log linear	-0.12(-0.85, 0.46)	1.94(0.94, 3.20)
Group ID Inverse	1.16(0.45, 1.78)	3.61(1.84, 6.32)
Democrat Disgust	*0.42(-0.09, 0.85)*	*0.81(-0.07, 2.01)*
Republican Disgust	0.84(0.45, 1.31)	1.31(0.39, 2.72)
Republican Disgust Square Root	0.52(0.07, 0.88)	0.75(0.06, 1.85)
Republican Disgust Log linear	*0.20(-0.26, 0.57)*	*0.43(-0.17, 1.52)*
Disgust	*0.43(-0.10, 0.90)*	*0.83(0.01, 2.78)*
Stereotype Content Model	*0.44(-0.67, 1.41)*	*3.65(2.11, 6.82)*
Perceived Emotion	0.79(0.35, 1.25)	1.17(0.15, 2.48)
Perceived Emotion Square Root	0.46(-0.002, 0.83)	0.48(-0.18, 1.47)

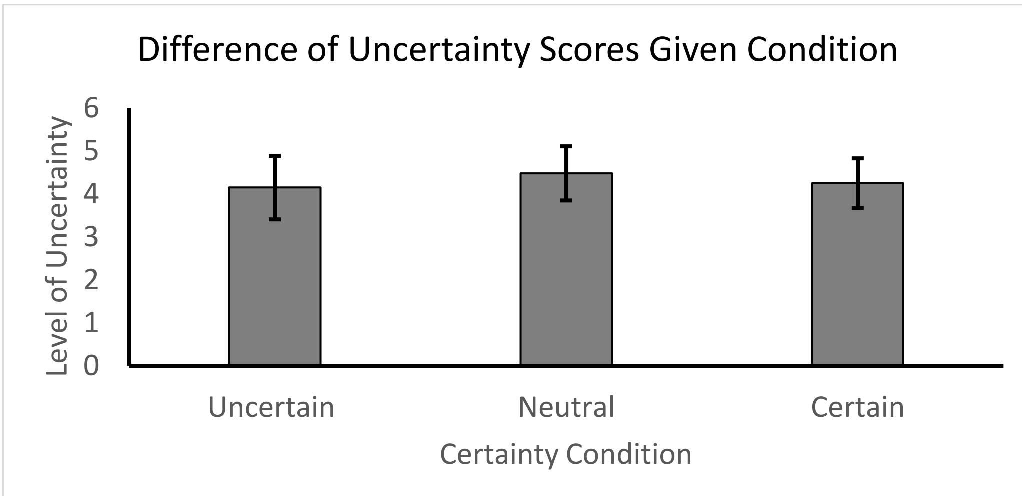
Variable	Skew	Kurtosis
Perceived Emotion Log linear	*0.13(-0.30, 0.51)*	*0.15(-0.37, 0.92)*

Integrity of the Uncertainty Prime.

To see if the uncertainty prime was efficacious, a single factor Analysis of Variance (ANOVA) was computed on uncertainty scores between condition (uncertain, certain, and neutral). While a Bartlett's test of homogeneity of variance was non-significant (p = .076), the ratio between groups were nearly tripled (49:126). Therefore, we utilized a Welch's corrected ANOVA. The omnibus test was significant (F(2,111) = 3.81, p = 0.025, η^2 = .03) showing real differences between conditions. However, a follow-up Tukey test of group comparisons yield only significance between certainty and uncertainty (95%CI (0.05, 0.61)). While there are significant differences between low and high uncertain conditions, their trends were opposite from expected as shown in Figure 3. The uncertain condition had lower uncertainty than the certain condition.

Figure 3

Difference in mean scores of uncertainty given priming conditions. There are only significant differences between the certainty (n = 49) and uncertainty (n = 69) conditions. Neutral (n = 126) was not significant across any groups. Errors bars presented indicate 95% confidence intervals.



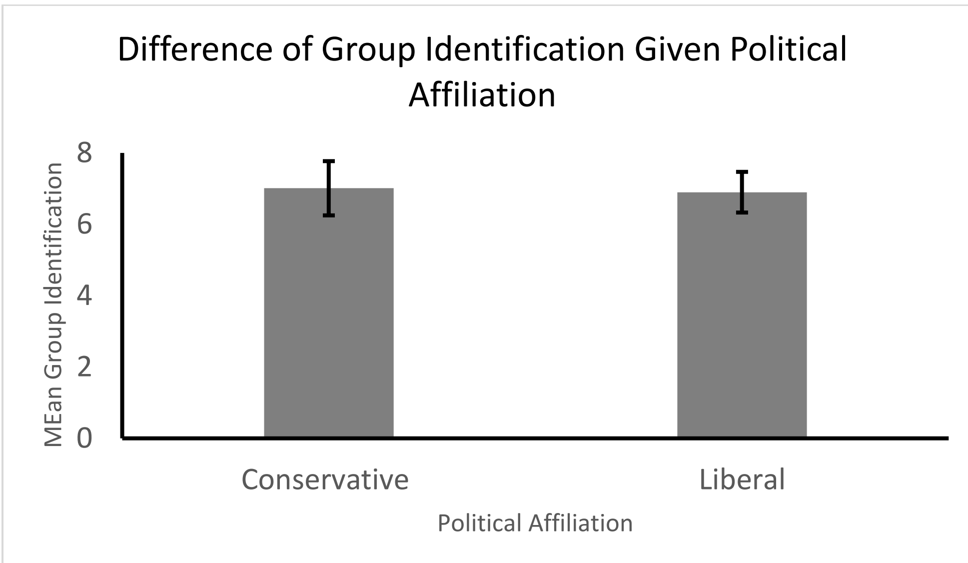
Confounds Potentially Present in the Design.

Given the nature of this experiment's complex design, there are a few confounds that can be tested and accounted for. First, there should be no differences between group identification with political parties because a difference indicates unbalanced experimental conditions where group identity serves as the independent variable. To test for this, group identification was compared between liberals and conservatives as well as among political parties. Given the disproportionate sample size between groups, all tests were conducted with a Welch's correction. There were no differences observed between liberal and conservative test-takers in their group identity as shown in figure 4: t(130.23)

= 1.20, p = .233, *Cohen's d* = 0.17. Furthermore, there were no differences observed for group identity among political party affiliation: $F(4,16.4) = 0.32$, $p = .862$, $\eta^2 = 0.003$.

Figure 4

Mean score of group identification given political affiliation. Political identity is in a forced dichotomization of conservative and liberal. There is no significant difference in group identity between liberal (n = 166) and conservative (n = 78) participants.

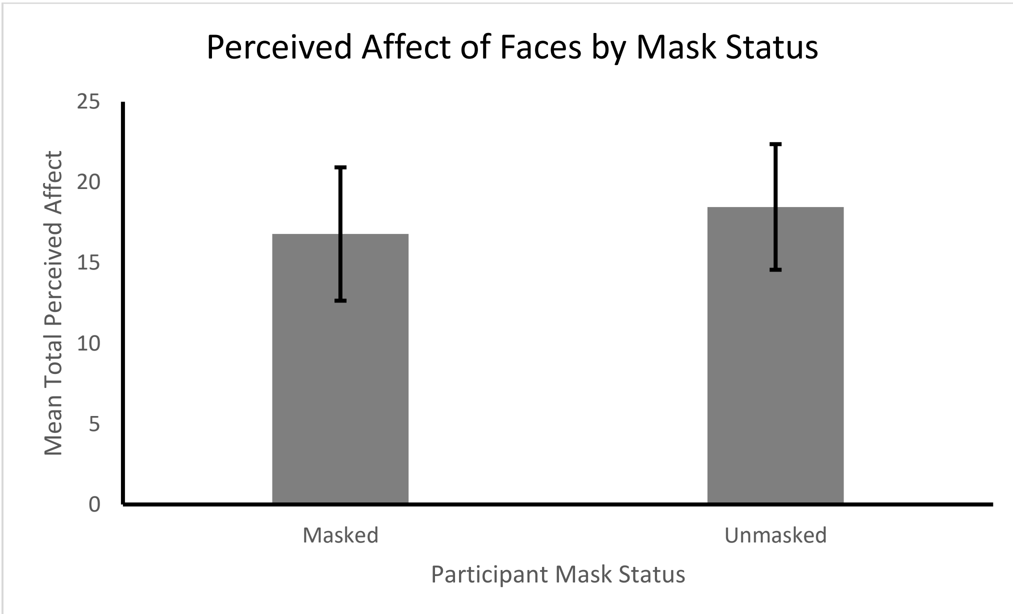


Affective Processing of Masked Faces

To see if affective processing is changed between masked and unmasked faces, I computed a pair-wise t-test between perceived affect on faces. I predicted that masked faces would viewed more negatively given their ambiguity. It was found that participants significantly viewed unmasked faces as more positively (M = 16.79, SD = 4.14) than unmasked faces (M = 18.47, SD = 3.91) in a paired t-test: $t(484.5) = -4.60$, $p < .001$, *Cohen's d* = 0.53 as represented in figure 5.

Figure 5

Mean perceived affect of experimental faces given the face's mask status. Masked faces are perceived to be exhibiting a more negative affect than unmasked faces (n = 244).



Hypothesis One

To test the mediation of emotional processing between uncertainty and risk perception, a Hayesian model 4 was conducted. Bootstrapped confidence intervals using Maximum Likelihood are provided below. I found that low amounts of uncertainty led to increased feelings towards others which in turn, predicted increasing risk perception. To break that down, lower levels of uncertainty is related to lower affect perceptions (95%*CI* (2.51, 18.31)) and lower risk perception (95%*CI* (0.11, 1.92)). Moreover, higher affect perception is also related to higher risk perception (95%*CI* (.007,0.04)). Facial processing of emotion mediates the relationship between uncertainty and risk perception (95%*CI* (0.05, 0.51)).

Given these results and the literature on uncertainty-identity theory, another mediation was computed testing the relationship between uncertainty, group identification, and risk perception. Uncertainty predicted both group identification (95%*CI* (0.14, 0.33)) and risk perception (95%*CI* (0.64, 2.05). Group identification also predicted risk perception (95%*CI* (1.20, 2.91)). Group identification moderately mediated the relationship at 95%*CI* (0.27, 0.89). The more uncertain one feels, the more they identify with their group, which in turn, increases risk perception.

Hypothesis Two

I also tested an alternative model seeing how group stereotype content mediates the relationship between group identification and risk. While higher group identification predicts higher perceived emotion in others (95%*CI* (6.56, 23.58)) and higher risk perception (95%*CI* (1.04, 2.38)), stereotype content is not related to risk perception (95%*CI* (-0.002, 0.02)). Further, stereotype content does not mediate this relationship (95%*CI* (-0.02, 0.28)).

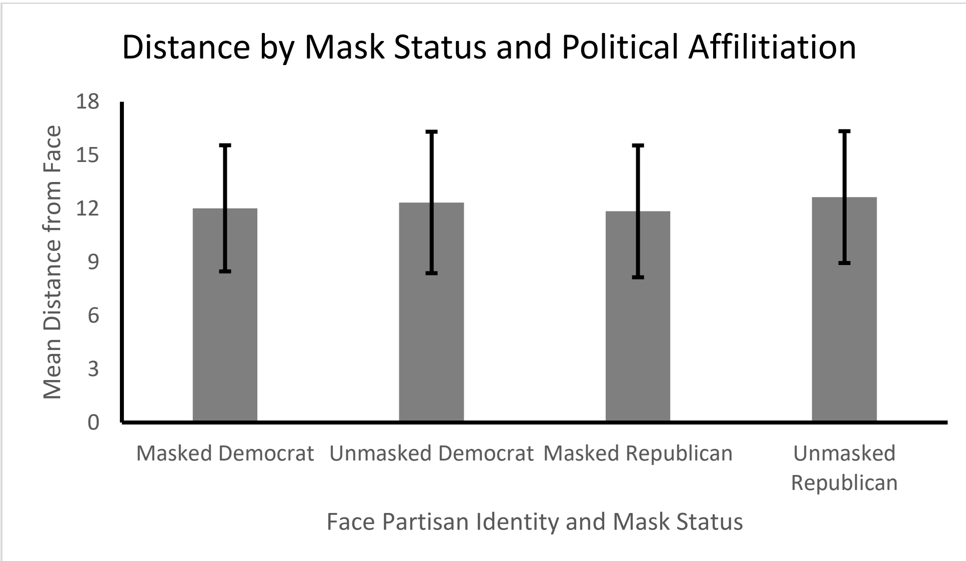
Hypothesis Three

A linear mixed model using Maximum Likelihood estimation was used to test the relationship between political identity of unmasked individuals and ratings of disgust. The participant's own identity was added as a covariate to see how political identity may dictate this relationship. The test of fixed effects was non-significant in a likelihood ratio test ($\chi^2(3) = 2.70$, p = .100) showing no difference in disgust ratings and the face's political identity. The test of random effects was also non-significant ($\chi^2(3) = 1.71$, p = .191). All participants perceived vulnerability to disease was not changed if the face was liberal or conservative. Furthermore, each participant's political leaning did not impact their disgust ratings of faces.

While disgust is commonly measured through the adapted Perceived Vulnerability to Disgust scale, we also included a measure of distance because of the protective factor distance has against COVID-19. Distance is a valuable measure of threat and, by proxy, disgust because differences in distance would indicate the person to be seen as a viable cause of infection. Given the previous model's non-significance, we performed an exploratory analysis on how mask status and political identity of the perceived face may change the participant's distance. A linear mixed model with Maximum Likelihood estimation was used to evaluate this effect. The test of fixed effects was significant ($\chi^2(7) = 28.11$, $p < .001$) indicating that mask status and political identity of the face changed how far people wished to distance themselves from said face. Follow-up pairwise comparisons using a Bonferroni corrected p value delineated the nature of this relationship showing no real differences between political identities but for mask status. While there is no difference in distance between a masked Republican and masked Democrat ($p = .918$), nor an unmasked Democrat and unmasked Republican ($p = .322$), there are significant distances between an unmasked Republican and a masked Democrat ($p = .005$) or Masked Republican ($p <.001$), and between a masked Republican and unmasked Democrat ($p = .023$). Participants wanted to stand farthest away from unmasked faces than masked faces regardless of political identity. The results are summarized below in Figure 6.

Figure 6

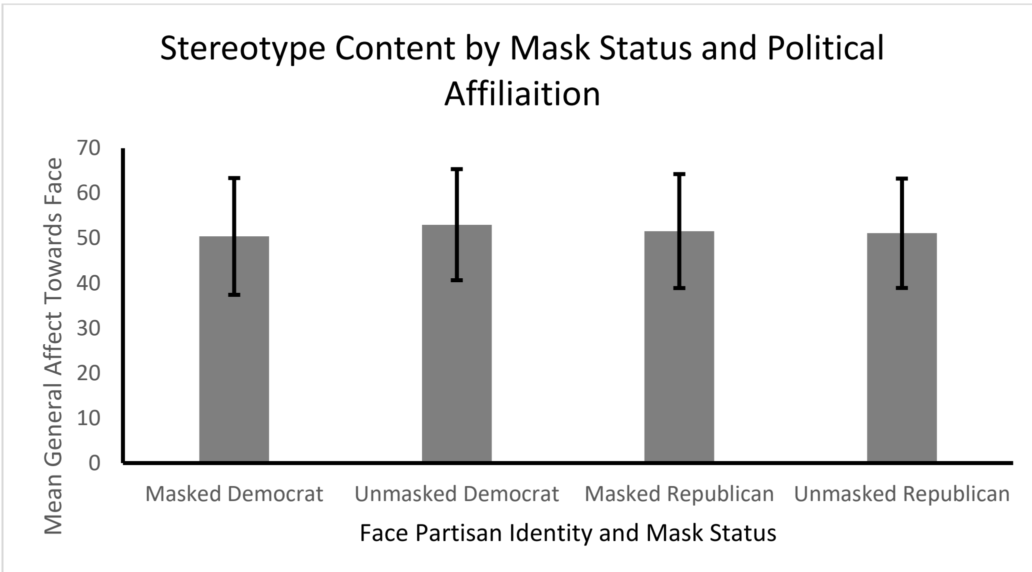
Chosen distance given face mask status and political identity. Participants wished to stand farthest from unmasked Republicans and closest to Masked Democrats (n = 244).



Another exploratory linear mixed model was tested evaluating general affect through stereotype content between mask status and political affiliation. The fixed effects were significant in a likelihood ratio test: $\chi^2(6) = 17.23$, p <.001. However, a test of comparisons found only significance between unmasked democrats and masked democrats (p = .001) as well as unmasked democrats and masked democrats (p = .013). Overall, unmasked Democrats were viewed as the most positive while masked Democrats were viewed as least positive regardless of own party biases as shown in Figure 7.

Figure 7

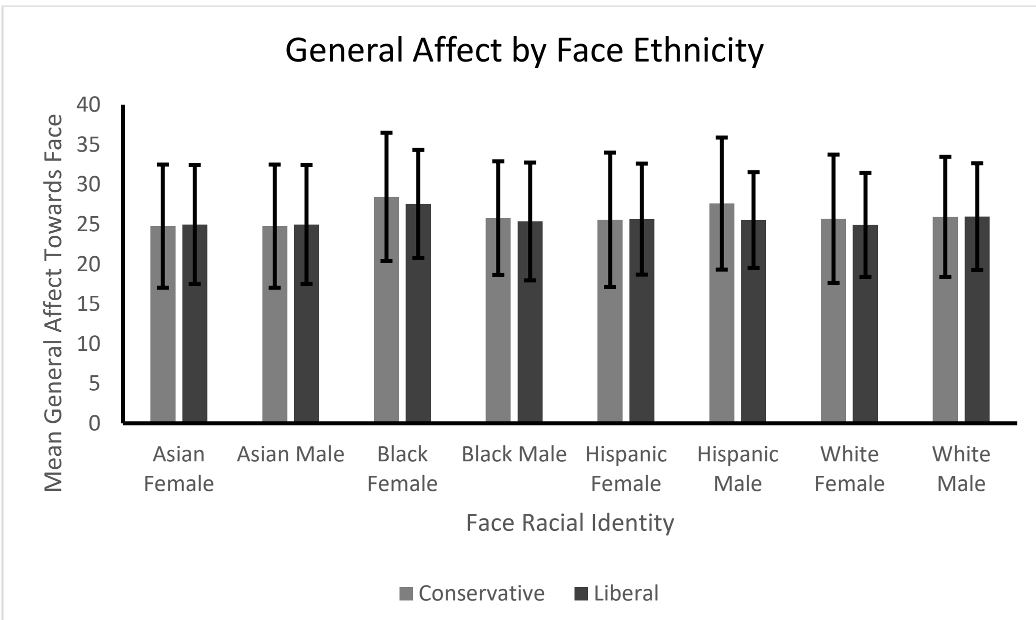
General affect towards face as measured by total Stereotype Content scores given face mask status and political identity (n = 244).



The above model failed to provide clear results, but the individual face's ethnicity was also tested explaining the model's ambiguity. The RADIATE face set is a unique tool for its ethnic diversity of experimental stimuli and the faces were randomly selected to a partisan identity during stimuli construction. Effects found could possibly be due to racially-biased processing of faces rather than group identification. A linear mixed model with Maximum Likelihood estimations was performed on stereotype content scores on each of the eight faces. The participant's political identity was used as a covariate to observe political biases. The fixed effects were found to be significant ($\chi^2(10) = 59.83$, *p* <.001) which indicates differences between general feelings towards each face seen in Figure 8. Additionally, the random effects were also significant ($\chi^2(10) = 29.94$, *p*<.001) showing that political leaning also matters in viewing faces. While a Bonferroni- adjusted t-test reveals no significant difference between any one conditisoin. All participants viewed Asian faces the least positively. The largest disparity observed between participant political identities were among the Hispanic male and white female face.

Figure 8

General affect towards face as measured by total Stereotype Content Scores between conservatives (n = 78) and liberals (n = 166).



Hypothesis Four

To test the way in which disgust mediates the relationship between group identification and risk perception, as well as the way uncertainty may moderate the mediation, a Hayesian model 7 was computed. Disgust was not predicted by group identification (95%*CI* (-3.49, 26.29)), uncertainty (95%*CI* (-12.92, 40.57)), nor their interaction (95%*CI* (-4.67, 2.5)). However, risk was associated with group identification (95%*CI* (0.13, 1.73)) and disgust (95%*CI* (0.08, 0.19)). While disgust did partially mediate the relationship between group identification and risk (95%*CI* (0.13, 1.30)), uncertainty was a poor moderator (95%*CI* (-0.72, 0.39)). Meaning that high group identification weakly leads to higher levels of disgust, which in turn leads to increased risk perception regardless of uncertainty.

When tested in model 4, group identification predicted both disgust (95%*CI* (4.93, 12.87) and risk perception (95%*CI* (0.54, 2.03). Disgust also positively predicts risk perception (95%*CI* (0.10, 0.16). Disgust moderately mediates the relationship between group identification and risk perception (95%*CI* (0.57, 2.10). Meaning, the more one identifies with a group, the more disgust they feel towards unmasked faces, which in turn, increases their awareness of risk.

Hypothesis Five

Finally, a moderated mediation was computed to see how perceived emotion mediates the relationship between community beliefs and risk perception, as well as how uncertainty moderates the mediation. Neither community belief (95%*CI* (-0.03, 0.03)), uncertainty (95%*CI* (-0.22, 0.21)), or their interaction (95%*CI* (-0.006, 0.007)) was related to perceived emotion. Further, while community belief did predict risk (0.03, 0.22) perceived emotion did not (95%*CI* (-21.43, 0.56)). The emotion participants perceived faces did not mediate the relationship between community beliefs and risk perception (95%*CI* (-0.02, 0.06)) and uncertainty did not moderate the mediation (95%*CI* (-0.11, 0.11)).

Discussion

The goal of this study was to delineate the components that propel individuals to undervalue the risk one may presently be in during the COVID-19 pandemic by what popular media has deemed “Caution Fatigue”. It was speculated that participants would undervalue risk based on shared group membership, emotional processing of masked faces, level of uncertainty, and the behavioral immune system. Ultimately, the current study fails to show evidence for this combined effect on risk with exception for individual factors.

Caution Fatigue

Results of this experiment fail to generate support for caution fatigue to be resultant of shared group membership. Cruwys and colleagues (2021) found that participants were willing to engage with risk when group membership was shared and members trusted their group. The pattern of findings here were somewhat reversed, such that group membership was related to increased disgust of COVID-19, and ultimately, risk perception. While our initial hypothesis posited different disgust scores by group membership, there was no significance observed. Both Democrats and Republicans felt the same amount of disgust no matter the unmasked face’s political leaning. A lot of this failure to find significance may largely be due to group identity saliency. As the pandemic has forced isolation, group identity may be stronger among members of closer systems such as friends or family members, not political compatriots.

Societal and cultural values may help to explain why people venture out during a pandemic in the face of such risk. Data collected in 2018 found a notable relationship between disease burden and individualistic societies (Morand & Walther, 2018). An individualistic society tends to experience more disease outbreak and burden than collectivist societies. These trends persist in the pandemic with research showing individualism is associated with higher infection rates and failure to engage in epidemic prophylaxis (Maaravi et al., 2021). While the processes of caution fatigue cannot be perfectly described in this experiment, protective factors to ensure safety of the self and the group were found. Rhetoric surrounding COVID-19 should focus on making some identity salient, clearly articulate group norms, and engage a level of disgust.

Behavioral Immune System is Sensitive to COVID-19

We found that the more one identifies with a group, the more disgust they feel towards unmasked faces, which in turn, increases the amount of risk to be perceived. This is in line with established findings showing behavioral immune system activation leading to collectivism and stringency to group norms (Murray & Schaller, 2011; Murray & Schaller, 2016). Within this framework, intergroup prejudices and denigration of deviant group members are also key behaviors. Although there were no significant differences between disgust of unmasked Democrat and Republican faces, this can largely be ascribed to mismatched experimental groupings; the participants were separated by liberal and conservative but the faces were Democrat and Republican. The lack of difference can be the result of liberal Republicans and conservative Democrats. We also lack the ability to compare disgust of a masked and unmasked face due to time-of-measurements being among unmasked faces. These analyses are ultimately lacking for their consideration of their identity as a liberal or conservative.

However, it is important to note there were differences observed between distance ratings by political party and mask status. Participants expressed a desire to stand farthest from unmasked Republicans and closest to masked Republicans. This finding was consistent regardless of the participant's own political identity too whether as liberal, conservative, Republican, or Democrat. This hints at prejudice under the behavioral immune system because of stereotypes associated with the Republican party and COVID-adherency. It's been well documented the connection between Republican-majority counties and infection rates as well as consumption of anti-masking rhetoric (Gollwitzer et al., 2020). Participants showed through distance that an unmasked Republican is one that poses a higher threat than a masked Republican which shows adherence to prescriptive group norms.

Xenophobia During the COVID-19 Pandemic

A unique finding to this study was measurements of feelings towards the presented faces being differentiated between ethnic identities. Participants felt most negatively towards Asian faces than any other ethnic identity. While attitudes towards ethnic minorities were not measured here directly, it is clear that Asian faces were not perceived as well as any other minority. Survey data conducted across 4,000 participants after the start of the COVID-19 pandemic reflect similar findings (Reny &Barretto, 2021). Fear of infection was found to be positively predictive of anti-Asian policies, attitudes, and behaviors. Additionally, a recent experiment modeled off federal messaging surrounding the virus found increased anti-Asian attitudes (Dhani & Franz, 2021). Experimental data shows that when presented with information regarding COVID's origin, economic threaht, and health concerns, participants were more likely to engage in anti-Asian rhetoric than when that information is not primed. These papers alongside the current study's findings are reminiscent of Faulkner and colleagues (2004) work finding increased perceived vulnerability to disease to promote xenophobic attitudes by proxy of the behavioral immune system. It was also shown in the current study that disgust and affect towards others would positively predict risk perception while participants also viewed Asian faces more negatively.

Limitations and Future Directions

There are inherent limitations to this survey design that restrict the data. Of note, the complex and within-subjects nature hinder true contrasts and control among observed effects. A between-subject experiment that tests masked versus unmasked against known political identity versus unknown would potentially provide more clear results. Separate experimental designs looking within ethnic identity and then facial processing would also benefit the literature. The complex interlaced nature of the current design overcomplicates many theoretical standings which make it difficult to extrapolate meaningful connections. As potential example of this, the uncertainty prime conducted worked contrarily to what was expected. Those in the certain condition exhibited higher levels of uncertainty to those in the uncertain condition. Unfortunately any analyses that include uncertainty are now ultimately null.

Additionally, the nature of participant recruitment has been recently put into question for concerns regarding data legitimacy and researcher security (Buhrmester, Talaifar, & Gosling, 2018). There are ways to improve the likelihood of success for this platform that was outside of this study's ability. Given additional funding, we would be able to pay higher rates for participation which includes a higher level of screening among participants. However, that too is associated with risks for participant fallacies to perform due to compensation. What more, at the time of experimentation is incredibly important. This study went live as vaccines were rolling out and becoming readily available. It would be entirely possible that we would find different results prior to any vaccine release.

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Appendices

Appendix A: Facial Stimuli

Figure 9

RADIATE faces used in the experiment. All faces are expressing neutral affect. Masks have been added by researchers.

Appendix B: Code Book

Data Tidying

Numbering Items

```
thesis$SocialPer_1<-as.numeric(thesis$SocialPer_1)
thesis$SocialPer_2<-as.numeric(thesis$SocialPer_2)
thesis$SocialPer_3<-as.numeric(thesis$SocialPer_3)
thesis$SocialPer_4<-as.numeric(thesis$SocialPer_4)
thesis$SocialPer_5<-as.numeric(thesis$SocialPer_5)
thesis$SocialPer_6<-as.numeric(thesis$SocialPer_6)
thesis$SocialPer_7<-as.numeric(thesis$SocialPer_7)
thesis$SocialPer_8<-as.numeric(thesis$SocialPer_8)

thesis$uncdv_1<-as.numeric(thesis$uncdv_1)
thesis$uncdv_2<-as.numeric(thesis$uncdv_2)
thesis$uncdv_3<-as.numeric(thesis$uncdv_3)
thesis$uncdv_4<-as.numeric(thesis$uncdv_4)
thesis$uncdv_5<-as.numeric(thesis$uncdv_5)

thesis$Lib.Group.ID_1<-as.numeric(thesis$Lib.Group.ID_1)
thesis$Lib.Group.ID_2<-as.numeric(thesis$Lib.Group.ID_2)
thesis$Lib.Group.ID_3<-as.numeric(thesis$Lib.Group.ID_3)
thesis$Lib.Group.ID_4<-as.numeric(thesis$Lib.Group.ID_4)
thesis$Lib.Group.ID_5<-as.numeric(thesis$Lib.Group.ID_5)
```

```
thesis$Lib.Group.ID_6<-as.numeric(thesis$Lib.Group.ID_6)

thesis$Lib.Group.ID_7<-as.numeric(thesis$Lib.Group.ID_7)

thesis$Lib.Group.ID_8<-as.numeric(thesis$Lib.Group.ID_8)

thesis$Lib.Group.ID_9<-as.numeric(thesis$Lib.Group.ID_9)


thesis$CON.ID_1<-as.numeric(thesis$CON.ID_1)

thesis$CON.ID_2<-as.numeric(thesis$CON.ID_2)

thesis$CON.ID_3<-as.numeric(thesis$CON.ID_3)

thesis$CON.ID_4<-as.numeric(thesis$CON.ID_4)

thesis$CON.ID_5<-as.numeric(thesis$CON.ID_5)

thesis$CON.ID_6<-as.numeric(thesis$CON.ID_6)

thesis$CON.ID_7<-as.numeric(thesis$CON.ID_7)

thesis$CON.ID_8<-as.numeric(thesis$CON.ID_8)

thesis$CON.ID_9<-as.numeric(thesis$CON.ID_9)


thesis$HF07.SCM1<-as.numeric(thesis$HF07.SCM1)

thesis$HF07.SCM2<-as.numeric(thesis$HF07.SCM2)

thesis$HF07.SCM3<-as.numeric(thesis$HF07.SCM3)

thesis$HF07.SCM.4<-as.numeric(thesis$HF07.SCM.4)

thesis$HF07.SCM.5<-as.numeric(thesis$HF07.SCM.5)

thesis$HF07.SCM.6<-as.numeric(thesis$HF07.SCM.6)

thesis$HF07.SCM.7<-as.numeric(thesis$HF07.SCM.7)

thesis$HF07.SCM.8<-as.numeric(thesis$HF07.SCM.8)
```

```
thesis$HF07.EMO<-as.numeric(thesis$HF07.EMO)

thesis$WF13.SCM.1<-as.numeric(thesis$WF13.SCM.1)
thesis$WF13.SCM.2<-as.numeric(thesis$WF13.SCM.2)
thesis$WF13.SCM.3<-as.numeric(thesis$WF13.SCM.3)
thesis$WF13.SCM.4<-as.numeric(thesis$WF13.SCM.4)
thesis$WF13.SCM.5<-as.numeric(thesis$WF13.SCM.5)
thesis$WF13.SCM.6<-as.numeric(thesis$WF13.SCM.6)
thesis$WF13.SCM.7<-as.numeric(thesis$WF13.SCM.7)
thesis$WF13.SCM.8<-as.numeric(thesis$WF13.SCM.8)

thesis$WF13.EMO<-as.numeric(thesis$WF13.EMO)

thesis$AF10.SCM.1<-as.numeric(thesis$AF10.SCM.1)
thesis$AF10.SCM.2<-as.numeric(thesis$AF10.SCM.2)
thesis$AF10.SCM.3<-as.numeric(thesis$AF10.SCM.3)
thesis$AF10.SCM.4<-as.numeric(thesis$AF10.SCM.4)
thesis$AF10.SCM.5<-as.numeric(thesis$AF10.SCM.5)
thesis$AF10.SCM.6<-as.numeric(thesis$AF10.SCM.6)
thesis$AF10.SCM.7<-as.numeric(thesis$AF10.SCM.7)
thesis$AF10.SCM.8<-as.numeric(thesis$AF10.SCM.8)
```

```
thesis$AF10.EMO<-as.numeric(thesis$AF10.EMO)


thesis$HM04.SCM.1<-as.numeric(thesis$HM04.SCM.1)
thesis$HM04.SCM.2<-as.numeric(thesis$HM04.SCM.2)
thesis$HM04.SCM.3<-as.numeric(thesis$HM04.SCM.3)
thesis$HM04.SCM.4<-as.numeric(thesis$HM04.SCM.4)
thesis$HM04.SCM.5<-as.numeric(thesis$HM04.SCM.5)
thesis$HM04.SCM.6<-as.numeric(thesis$HM04.SCM.6)
thesis$HM04.SCM.7<-as.numeric(thesis$HM04.SCM.7)
thesis$HM04.SCM.8<-as.numeric(thesis$HM04.SCM.8)


thesis$HM04.EMO<-as.numeric(thesis$HM04.EMO)


thesis$BM13.SCM.1<-as.numeric(thesis$BM13.SCM.1)
thesis$BM13.SCM.2<-as.numeric(thesis$BM13.SCM.2)
thesis$BM13.SCM.3<-as.numeric(thesis$BM13.SCM.3)
thesis$BM13.SCM.4<-as.numeric(thesis$BM13.SCM.4)
thesis$BM13.SCM.5<-as.numeric(thesis$BM13.SCM.5)
thesis$BM13.SCM.6<-as.numeric(thesis$BM13.SCM.6)
thesis$BM13.SCM.7<-as.numeric(thesis$BM13.SCM.7)
thesis$BM13.SCM.8<-as.numeric(thesis$BM13.SCM.8)


thesis$BM13.EMO<-as.numeric(thesis$BM13.EMO)
```

```
thesis$AM05.SCM.1<-as.numeric(thesis$AM05.SCM.1)
thesis$AM05.SCM.2<-as.numeric(thesis$AM05.SCM.2)
thesis$AM05.SCM.3<-as.numeric(thesis$AM05.SCM.3)
thesis$AM05.SCM.4<-as.numeric(thesis$AM05.SCM.4)
thesis$AM05.SCM.5<-as.numeric(thesis$AM05.SCM.5)
thesis$AM05.SCM.6<-as.numeric(thesis$AM05.SCM.6)
thesis$AM05.SCM.7<-as.numeric(thesis$AM05.SCM.7)
thesis$AM05.SCM.8<-as.numeric(thesis$AM05.SCM.8)

thesis$AM05.EMO<-as.numeric(thesis$AM05.EMO)

thesis$WM13.SCM.1<-as.numeric(thesis$WM13.SCM.1)
thesis$WM13.SCM.2<-as.numeric(thesis$WM13.SCM.2)
thesis$WM13.SCM.3<-as.numeric(thesis$WM13.SCM.3)
thesis$WM13.SCM.4<-as.numeric(thesis$WM13.SCM.4)
thesis$WM13.SCM.5<-as.numeric(thesis$WM13.SCM.5)
thesis$WM13.SCM.6<-as.numeric(thesis$WM13.SCM.6)
thesis$WM13.SCM.7<-as.numeric(thesis$WM13.SCM.7)
thesis$WM13.SCM.8<-as.numeric(thesis$WM13.SCM.8)

thesis$WM13.EMO<-as.numeric(thesis$WM13.EMO)
```

```
thesis$BF03.SCM.1<-as.numeric(thesis$BF03.SCM.1)

thesis$BF03.SCM.2<-as.numeric(thesis$BF03.SCM.2)

thesis$BF03.SCM.3<-as.numeric(thesis$BF03.SCM.3)

thesis$BF03.SCM.4<-as.numeric(thesis$BF03.SCM.4)

thesis$BF03.SCM.5<-as.numeric(thesis$BF03.SCM.5)

thesis$BF03.SCM.6<-as.numeric(thesis$BF03.SCM.6)

thesis$BF03.SCM.7<-as.numeric(thesis$BF03.SCM.7)

thesis$BF03.SCM.8<-as.numeric(thesis$BF03.SCM.8)


thesis$BF03.EMO<-as.numeric(thesis$BF03.EMO)


thesis$DEM.DISGUST.1<-as.numeric(thesis$DEM.DISGUST.1)

thesis$DEM.DISGUST.2<-as.numeric(thesis$DEM.DISGUST.2)

thesis$DEM.DISGUST.3<-as.numeric(thesis$DEM.DISGUST.3)

thesis$DEM.DISGUST.4<-as.numeric(thesis$DEM.DISGUST.4)

thesis$DEM.DISGUST.5<-as.numeric(thesis$DEM.DISGUST.5)

thesis$DEM.DISGUST.6<-as.numeric(thesis$DEM.DISGUST.6)

thesis$DEM.DISGUST.7<-as.numeric(thesis$DEM.DISGUST.7)

thesis$DEM.DISGUST.8<-as.numeric(thesis$DEM.DISGUST.8)

thesis$DEM.DISGUST.9<-as.numeric(thesis$DEM.DISGUST.9)

thesis$DEM.DISGUST.10<-as.numeric(thesis$DEM.DISGUST.10)

thesis$DEM.DISGUST.11<-as.numeric(thesis$DEM.DISGUST.11)

thesis$DEM.DISGUST.12<-as.numeric(thesis$DEM.DISGUST.12)
```

```
thesis$DEM.DISGUST.13<-as.numeric(thesis$DEM.DISGUST.13)

thesis$DEM.DISGUST.14<-as.numeric(thesis$DEM.DISGUST.14)

thesis$DEM.DISGUST.15<-as.numeric(thesis$DEM.DISGUST.15)


thesis$REPUB.DISGUST.1<-as.numeric(thesis$REPUB.DISGUST.1)

thesis$REPUB.DISGUST.2<-as.numeric(thesis$REPUB.DISGUST.2)

thesis$REPUB.DISGUST.3<-as.numeric(thesis$REPUB.DISGUST.3)

thesis$REPUB.DISGUST.4<-as.numeric(thesis$REPUB.DISGUST.4)

thesis$REPUB.DISGUST.5<-as.numeric(thesis$REPUB.DISGUST.5)

thesis$REPUB.DISGUST.6<-as.numeric(thesis$REPUB.DISGUST.6)

thesis$REPUB.DISGUST.7<-as.numeric(thesis$REPUB.DISGUST.7)

thesis$REPUB.DISGUST.8<-as.numeric(thesis$REPUB.DISGUST.8)

thesis$REPUB.DISGUST.9<-as.numeric(thesis$REPUB.DISGUST.9)

thesis$REPUB.DISGUST.10<-as.numeric(thesis$REPUB.DISGUST.10)

thesis$REPUB.DISGUST.11<-as.numeric(thesis$REPUB.DISGUST.11)

thesis$REPUB.DISGUST.12<-as.numeric(thesis$REPUB.DISGUST.12)

thesis$REPUB.DISGUST.13<-as.numeric(thesis$REPUB.DISGUST.13)

thesis$REPUB.DISGUST.14<-as.numeric(thesis$REPUB.DISGUST.14)

thesis$REPUB.DISGUST.15<-as.numeric(thesis$REPUB.DISGUST.15)


thesis$Risk_1<-as.numeric(thesis$Risk_1)

thesis$Risk_2<-as.numeric(thesis$Risk_2)

thesis$Risk_3<-as.numeric(thesis$Risk_3)
```

```
thesis$Risk_4<-as.numeric(thesis$Risk_4)


thesis$COVID.beliefs_1<-as.numeric(thesis$COVID.beliefs_1)
thesis$COVID.beliefs_2<-as.numeric(thesis$COVID.beliefs_2)
thesis$COVID.beliefs_3<-as.numeric(thesis$COVID.beliefs_3)
thesis$COVID.beliefs_4<-as.numeric(thesis$COVID.beliefs_4)
thesis$COVID.beliefs_5<-as.numeric(thesis$COVID.beliefs_5)
thesis$COVID.beliefs_6<-as.numeric(thesis$COVID.beliefs_6)
thesis$COVID.beliefs_7<-as.numeric(thesis$COVID.beliefs_7)
thesis$COVID.beliefs_8<-as.numeric(thesis$COVID.beliefs_8)
thesis$COVID.beliefs_9<-as.numeric(thesis$COVID.beliefs_9)
thesis$COVID.beliefs_10<-as.numeric(thesis$COVID.beliefs_10)
```

Reverse Scoring of Items

```
library(car)

## Loading required package: carData

thesis$SocialPer_1<- recode(thesis$SocialPer_1, "1=7; 2=6; 3=5; 4=4;
5=3; 6=2; 7=1" )
thesis$SocialPer_4<- recode(thesis$SocialPer_2,"1=7; 2=6; 3=5; 4=4; 5=3
; 6=2; 7=1")
thesis$SocialPer_6<- recode(thesis$SocialPer_4, "1=7; 2=6; 3=5; 4=4; 5=
3; 6=2; 7=1")
thesis$SocialPer_7<- recode(thesis$SocialPer_7, "1=7; 2=6; 3=5; 4=4; 5=
```

```
3; 6=2; 7=1")


thesis$DEM.DISGUST.3<- recode(thesis$DEM.DISGUST.3, "1=7; 2=6; 3=5; 4=4
; 5=3; 6=2; 7=1")
thesis$DEM.DISGUST.5<- recode(thesis$DEM.DISGUST.5, "1=7; 2=6; 3=5; 4=4
; 5=3; 6=2; 7=1")
thesis$DEM.DISGUST.11<- recode(thesis$DEM.DISGUST.11, "1=7; 2=6; 3=5; 4
=4; 5=3; 6=2; 7=1")
thesis$DEM.DISGUST.12<- recode(thesis$DEM.DISGUST.12, "1=7; 2=6; 3=5; 4
=4; 5=3; 6=2; 7=1")
thesis$DEM.DISGUST.13<- recode(thesis$DEM.DISGUST.13, "1=7; 2=6; 3=5; 4
=4; 5=3; 6=2; 7=1")
thesis$DEM.DISGUST.14<- recode(thesis$DEM.DISGUST.14, "1=7; 2=6; 3=5; 4
=4; 5=3; 6=2; 7=1")


thesis$REPUB.DISGUST.3<-recode(thesis$REPUB.DISGUST.3, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$REPUB.DISGUST.5<- recode(thesis$DEM.DISGUST.5, "1=7; 2=6; 3=5; 4
=4; 5=3; 6=2; 7=1")
thesis$REPUB.DISGUST.11<- recode(thesis$DEM.DISGUST.11, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$REPUB.DISGUST.12<- recode(thesis$DEM.DISGUST.12, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
```

```
thesis$REPUB.DISGUST.13<- recode(thesis$DEM.DISGUST.13, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$REPUB.DISGUST.14<- recode(thesis$DEM.DISGUST.14, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")


thesis$COVID.beliefs_3<-recode(thesis$COVID.beliefs_3, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$COVID.beliefs_4<- recode(thesis$COVID.beliefs_4, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$COVID.beliefs_6<- recode(thesis$COVID.beliefs_6, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$COVID.beliefs_7<- recode(thesis$COVID.beliefs_7, "1=7; 2=6; 3=5;
4=4; 5=3; 6=2; 7=1")
thesis$COVID.beliefs_10<- recode(thesis$COVID.beliefs_10, "1=7; 2=6; 3=
5; 4=4; 5=3; 6=2; 7=1")
```

Creating Factors and Composite Variables

```
thesis$Cert_Cond<-factor(thesis$Cert_Cond, levels = c(1:3))
levels(thesis$Cert_Cond)[1]<-"Uncertainty"
levels(thesis$Cert_Cond)[2]<-"Certainty"
levels(thesis$Cert_Cond)[3]<-"Neutral"


library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following object is masked from 'package:car':
##
##     recode

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

thesis<-thesis %>%
  mutate(pol.leaning_3 = as.character(pol.leaning_3),
         pol.leaning_3 = as.numeric(pol.leaning_3),
         POLID = case_when(
           pol.leaning_3 < 5 ~ "Conservative",
           pol.leaning_3 > 4 ~ "Liberal"))
thesis$POLID<-as.factor(thesis$POLID)


#Risk Perception#
thesis$risk<-thesis$Risk_1+thesis$Risk_2+thesis$Risk_3+thesis$Risk_4
```

```
#Uncertainty Scale#
thesis$unc<-thesis$uncdv_1+thesis$uncdv_2+thesis$uncdv_3+thesis$uncdv_4
+thesis$uncdv_5

#Social Perception#
thesis$combelief<-thesis$SocialPer_1+thesis$SocialPer_2+thesis$SocialPe
r_3+thesis$SocialPer_4+thesis$SocialPer_5+
  thesis$SocialPer_6+thesis$SocialPer_7+thesis$SocialPer_8

#Group ID#
thesis$groupid<-thesis$Lib.Group.ID_1+thesis$Lib.Group.ID_2+thesis$Lib.
Group.ID_3+thesis$Lib.Group.ID_4+
  thesis$Lib.Group.ID_5+thesis$Lib.Group.ID_6+ thesis$Lib.Group.ID_7+th
esis$Lib.Group.ID_8+
  thesis$Lib.Group.ID_9+thesis$CON.ID_1+thesis$CON.ID_2+thesis$CON.ID_3
+thesis$CON.ID_4+thesis$CON.ID_5+
  thesis$CON.ID_6+thesis$CON.ID_7+thesis$CON.ID_8+thesis$CON.ID_9

#Democrat Disgust#
thesis$demdis<- thesis$DEM.DISGUST.1+thesis$DEM.DISGUST.2+thesis$DEM.DI
SGUST.3+thesis$DEM.DISGUST.4+
  thesis$DEM.DISGUST.5+thesis$DEM.DISGUST.6+thesis$DEM.DISGUST.7+thesis
$DEM.DISGUST.8+thesis$DEM.DISGUST.9+
```

```
  thesis$DEM.DISGUST.10+thesis$DEM.DISGUST.11+thesis$DEM.DISGUST.12+the
sis$DEM.DISGUST.13+thesis$DEM.DISGUST.14+
  thesis$DEM.DISGUST.15

#Republican Disgust#
thesis$repdis<- thesis$REPUB.DISGUST.1+thesis$REPUB.DISGUST.2+thesis$RE
PUB.DISGUST.3+thesis$REPUB.DISGUST.4+
  thesis$REPUB.DISGUST.5+thesis$REPUB.DISGUST.6+thesis$REPUB.DISGUST.7+
thesis$REPUB.DISGUST.8+
  thesis$REPUB.DISGUST.9+thesis$REPUB.DISGUST.10+thesis$REPUB.DISGUST.1
1+thesis$REPUB.DISGUST.12+
  thesis$REPUB.DISGUST.13+thesis$REPUB.DISGUST.14+thesis$REPUB.DISGUST.
15

#COVID Beliefs#
thesis$covidbel<-thesis$COVID.beliefs_1+thesis$COVID.beliefs_2+thesis$C
OVID.beliefs_3+thesis$COVID.beliefs_4+
  thesis$COVID.beliefs_5+thesis$COVID.beliefs_6+thesis$COVID.beliefs_7+
thesis$COVID.beliefs_8+
  thesis$COVID.beliefs_9+thesis$COVID.beliefs_10

#Resepective Face SCM#
thesis$HFSCM<-thesis$HF07.SCM1+thesis$HF07.SCM2+thesis$HF07.SCM3+thesis
```

```
$HF07.SCM.4+thesis$HF07.SCM.5+
  thesis$HF07.SCM.6+thesis$HF07.SCM.7+thesis$HF07.SCM.8

thesis$WFSCM<-thesis$WF13.SCM.1+thesis$WF13.SCM.2+thesis$AF10.SCM.3+the
sis$WF13.SCM.4+thesis$WF13.SCM.5+
  thesis$WF13.SCM.6+thesis$WF13.SCM.7+thesis$WF13.SCM.8

thesis$AFSCM<-thesis$AF10.SCM.1+thesis$AF10.SCM.2+thesis$AF10.SCM.3+the
sis$AF10.SCM.4+thesis$AF10.SCM.5+
  thesis$AF10.SCM.6+thesis$AF10.SCM.7+thesis$AF10.SCM.8

thesis$HMSCM<-thesis$HM04.SCM.1+thesis$HM04.SCM.2+thesis$HM04.SCM.3+the
sis$HM04.SCM.4+thesis$HM04.SCM.5+
  thesis$HM04.SCM.6+thesis$HM04.SCM.7+thesis$HM04.SCM.8

thesis$BMSCM<- thesis$BM13.SCM.1+thesis$BM13.SCM.2+thesis$BM13.SCM.3+th
esis$BM13.SCM.4+thesis$BM13.SCM.5+
  thesis$BM13.SCM.6+thesis$BM13.SCM.7+thesis$BM13.SCM.8

thesis$AMSCM<- thesis$AF10.SCM.1+thesis$AF10.SCM.2+thesis$AF10.SCM.3+th
esis$AF10.SCM.4+thesis$AF10.SCM.5+
  thesis$AF10.SCM.6+thesis$AF10.SCM.7+thesis$AF10.SCM.8
```

```
thesis$WMSCM<- thesis$WM13.SCM.1+thesis$WM13.SCM.2+thesis$WM13.SCM.3+th
esis$WM13.SCM.4+thesis$WM13.SCM.5+
  thesis$WM13.SCM.6+thesis$WM13.SCM.7+thesis$WM13.SCM.8

thesis$BFSCM<- thesis$BF03.SCM.1+thesis$BF03.SCM.2+thesis$BF03.SCM.3+th
esis$BF03.SCM.4+thesis$BF03.SCM.5+
  thesis$BF03.SCM.6+thesis$BF03.SCM.7+thesis$BF03.SCM.8

#SCM Overall#
thesis$SCM<-thesis$HFSCM+thesis$WFSCM+thesis$AFSCM+thesis$HMSCM+thesis$
BMSCM+thesis$AMSCM+thesis$WMSCM+
  thesis$BFSCM

#SCM Democrat#
thesis$DEMSCM<-thesis$WFSCM+thesis$AFSCM+thesis$BMSCM+thesis$BFSCM

#SCM Republican#
thesis$REPSCM<-thesis$HFSCM+thesis$HMSCM+thesis$AMSCM+thesis$WMSCM

#SCM Unmasked#
thesis$UMSCM<-thesis$WFSCM+thesis$HMSCM+thesis$AMSCM+thesis$BFSCM

#SCM Masked#
```

```
thesis$MSCM<-thesis$HFSCM+thesis$AFSCM+thesis$BMSCM+thesis$WMSCM

#SCM Unmasked Republican#
thesis$UMRSCM<-thesis$HMSCM+thesis$AMSCM

#SCM Masked Republican#
thesis$MRSCM<-thesis$HFSCM+thesis$WMSCM

#SCM Unmasked Democrat#
thesis$UMDSCM<-thesis$WFSCM+thesis$BFSCM

#SCM Maksed Democrat#
thesis$MDSCM<- thesis$AFSCM+thesis$BMSCM

#Masked Distance#
thesis$MDIST<-thesis$AF10.SOCIAL.DIST+thesis$BM13.SOCIAL.DIST+thesis$HF
07.Social.Distance+thesis$WM13.SOCIAL.DIST

#Unmasked Distance#
thesis$UMDIST<-thesis$WF13.SOCIAL.DIST+thesis$BF03.SOCIAL.DIST+thesis$H
M04.SOCIAL.DIST+thesis$AM05.SOCIAL.DIST

#Democrat Distance#
```

```
thesis$DEMDIST<-thesis$WF13.SOCIAL.DIST+thesis$AF10.SOCIAL.DIST+thesis$
BM13.SOCIAL.DIST+thesis$BF03.SOCIAL.DIST

#Republican Distance#
thesis$REPDIST<-thesis$HF07.Social.Distance+thesis$HM04.SOCIAL.DIST+the
sis$AM05.SOCIAL.DIST+thesis$WM13.SOCIAL.DIST

#Masked Democrat Distance#
thesis$MDDIST<-thesis$AF10.SOCIAL.DIST+thesis$BM13.SOCIAL.DIST

#Unmasked Democrat Distance#
thesis$UMDDIST<-thesis$WF13.SOCIAL.DIST+thesis$BF03.SOCIAL.DIST

#Masked Republican Distance#
thesis$MRDIST<- thesis$HF07.Social.Distance+thesis$WM13.SOCIAL.DIST

#Unmasked Republican Distance#
thesis$UMRDIST<- thesis$HM04.SOCIAL.DIST+thesis$AM05.SOCIAL.DIST

#Emotion Overall#
thesis$EMO<-thesis$AF10.EMO+thesis$AM05.EMO+thesis$BF03.EMO+thesis$BM13
.EMO+thesis$HF07.EMO+thesis$HM04.EMO+
  thesis$WF13.EMO+thesis$WM13.EMO
```

```
#Emotion Masked#
thesis$ME<- thesis$AF10.EMO+thesis$BM13.EMO+thesis$HF07.EMO+thesis$WM13
.EMO

#Emotion Unmasked#
thesis$UME<- thesis$WF13.EMO+thesis$BF03.EMO+thesis$HM04.EMO+thesis$AM0
5.EMO

#Emotion Democrat Masked#
thesis$MDE<- thesis$AF10.EMO+thesis$BM13.EMO

#Emotion Democrat Unmasked#
thesis$UMDE<- thesis$WF13.EMO+thesis$BF03.EMO

#Emotion Republican Masked#
thesis$MRE<-thesis$HF07.EMO+thesis$WM13.EMO

#Emotion Republican Unmasked#
thesis$UMRE<-thesis$HM04.EMO+thesis$AM05.EMO

#Timing#
thesis$timing<-thesis$Duration..in.seconds.
```

Creating a new workable dataset

```
cautionfatigue<-subset(thesis, select = c(age, ethnicity, Education,
gender, party,
                           timing, County.Travel, State.Travel, Country
.Travel,
                           VACCINE, Vaccine.intent, POLID, Cert_Cond,un
c,
                           risk, combelief, groupid, demdis, repdis,
                           covidbel, SCM, DEMSCM, REPSCM, UMSCM, MSCM,
                           UMRSCM, MRSCM, UMDSCM, MDSCM, MDIST, UMDIST,
MDDIST, UMDDIST,
                           MRDIST, UMRDIST,DEMDIST, REPDIST, EMO, ME,
                           UME, MDE, UMDE, MRE, UMRE,HFSCM,WFSCM, AFSCM
,HMSCM,BMSCM,AMSCM,
                           WMSCM,BFSCM,WF13.SOCIAL.DIST,AF10.SOCIAL.DIS
T,
                           BM13.SOCIAL.DIST,BF03.SOCIAL.DIST,HF07.Socia
l.Distance,
                           HM04.SOCIAL.DIST,AM05.SOCIAL.DIST,WM13.SOCIA
L.DIST))
```

Listwise deletion of incomplete cases

```
cautionfatigue<-na.omit(cautionfatigue)
#Went from n of 249 to n of 244
```

Data Normalcy

Skew and Kurtosis Estimates

```
DescTools::Skew(cautionfatigue$unc,method =2,conf.level =.99)

##      skew    lwr.ci    upr.ci
## 0.7445326 0.3147751 1.1532847

DescTools::Kurt(cautionfatigue$unc, method =2,conf.level =.99)

##      kurt    lwr.ci    upr.ci
## 1.0541662 0.2731606 2.5028420

#Transform
cautionfatigue$uncsqt<-(cautionfatigue$unc+1)^0.5
DescTools::Skew(cautionfatigue$uncsqt,method =2,conf.level =.99 )

##       skew     lwr.ci     upr.ci
##  0.1309193 -0.3580491  0.6083984

DescTools::Kurt(cautionfatigue$uncsqt, method =2,conf.level =.99)

##      kurt    lwr.ci    upr.ci
## 0.9114988 0.1845354 1.9479897
```

```
   cautionfatigue$unclg<-log10(cautionfatigue$unc+1)
DescTools::Skew(cautionfatigue$unclg, method =2,conf.level =.99)

   ##        skew      lwr.ci      upr.ci
## -0.62189619 -1.15109966  0.03940316

   DescTools::Kurt(cautionfatigue$unclg, method =2,conf.level =.99)

   ##      kurt    lwr.ci    upr.ci
## 1.9679065 0.5957796 3.5034478

   cautionfatigue$uncin<-(1/(cautionfatigue$unc+1))
DescTools::Skew(cautionfatigue$uncin, method =2,conf.level =.99)

   ##     skew   lwr.ci   upr.ci
## 2.551705 1.472869 3.176926

   DescTools::Kurt(cautionfatigue$uncin, method =2,conf.level =.99)

   ##      kurt    lwr.ci    upr.ci
##  9.888546  5.624085 16.413164

   cautionfatigue$unc<-cautionfatigue$uncsqt
#########
DescTools::Skew(cautionfatigue$combelief, method =2,conf.level =.99)

   ##       skew      lwr.ci     upr.ci
##  0.2648955 -0.1601661  0.7012725
```

```
DescTools::Kurt(cautionfatigue$combelief, method =2,conf.level =.99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics use
d as
## endpoints

##       kurt     lwr.ci     upr.ci
##  0.3707570 -0.3228604  1.5405335

#########
DescTools::Skew(cautionfatigue$groupid, method =2,conf.level =.99)

##      skew    lwr.ci    upr.ci
## 0.8384011 0.2599194 1.4888162

DescTools::Kurt(cautionfatigue$groupid, method =2,conf.level =.99)

##     kurt   lwr.ci   upr.ci
## 2.359125 1.130834 4.617654

#transform
cautionfatigue$groupidsq<-(cautionfatigue$groupid+1)^0.5
DescTools::Skew(cautionfatigue$groupidsq, method =2,conf.level =.99)

##       skew     lwr.ci     upr.ci
##  0.3662779 -0.2375575  1.0002778

DescTools::Kurt(cautionfatigue$groupidsq, method =2,conf.level =.99)
```

```
##      kurt    lwr.ci    upr.ci
## 1.9057012 0.8973209 3.2722122

cautionfatigue$groupidlg<-log10(cautionfatigue$groupid+1)
DescTools::Skew(cautionfatigue$groupidlg, method =2,conf.level =.99)

##       skew     lwr.ci     upr.ci
## -0.1288134 -0.7486722  0.4954156

DescTools::Kurt(cautionfatigue$groupidl, method =2,conf.level =.99)

##     kurt   lwr.ci   upr.ci
## 1.937438 1.030158 3.405550

cautionfatigue$groupidin<- (1/(cautionfatigue$groupid+1))
DescTools::Skew(cautionfatigue$groupidin, method =2,conf.level =.99)

##      skew    lwr.ci    upr.ci
## 1.1618251 0.1903366 1.7326490

DescTools::Kurt(cautionfatigue$groupidin, method =2,conf.level =.99)

##     kurt   lwr.ci   upr.ci
## 3.614170 1.798339 5.998592

cautionfatigue$groupid<-cautionfatigue$groupidsq
#########
DescTools::Skew(cautionfatigue$demdis, method =2,conf.level =.99)
```

```
##        skew      lwr.ci      upr.ci
##  0.42133087 -0.02720847  0.95269993

DescTools::Kurt(cautionfatigue$demdis, method =2,conf.level =.99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics use
d as
## endpoints

##        kurt      lwr.ci      upr.ci
##  0.81396759 -0.01648322  2.07805712

#########
DescTools::Skew(cautionfatigue$repdis, method =2,conf.level =.99)

##      skew    lwr.ci    upr.ci
## 0.8411334 0.3764949 1.2109525

DescTools::Kurt(cautionfatigue$repdis, method =2,conf.level =.99)

##      kurt    lwr.ci    upr.ci
## 1.3132472 0.3769576 2.5897445

#Transform
cautionfatigue$repdissqt<-(cautionfatigue$repdis+1)^0.5
DescTools::Skew(cautionfatigue$repdissqt, method =2,conf.level =.99)
```

```
## skew lwr.ci upr.ci
## 0.51814445 0.08953162 0.84904625

DescTools::Kurt(cautionfatigue$repdissqt, method =2,conf.level =.99)

## kurt lwr.ci upr.ci
## 0.7466060 0.0761108 1.7071585

cautionfatigue$repdislg<-log10(cautionfatigue$repdis+1)
DescTools::Skew(cautionfatigue$repdislg, method =2,conf.level =.99)

## skew lwr.ci upr.ci
## 0.2020619 -0.2404899 0.5571542

DescTools::Kurt(cautionfatigue$repdislg, method =2,conf.level =.99)

## kurt lwr.ci upr.ci
## 0.4317817 -0.1886220 1.4093406

#########
cautionfatigue$disgust<-cautionfatigue$demdis+cautionfatigue$repdis
DescTools::Skew(cautionfatigue$disgust, method =2,conf.level =.99)

## skew lwr.ci upr.ci
## 1.0625952 0.5131924 1.5109470

DescTools::Kurt(cautionfatigue$disgust, method =2,conf.level =.99)
```

```
##      kurt    lwr.ci    upr.ci
## 2.1637476 0.8250468 3.8611629

############
DescTools::Skew(cautionfatigue$SCM, method =2,conf.level =.99)

##       skew     lwr.ci     upr.ci
##  0.4361540 -0.5541729  1.5367308

DescTools::Kurt(cautionfatigue$SCM, method =2,conf.level =.99)

##     kurt   lwr.ci   upr.ci
## 3.653477 2.128969 6.581298

############
DescTools::Skew(cautionfatigue$EMO, method =2,conf.level =.99)

##      skew    lwr.ci    upr.ci
## 0.7950969 0.3127669 1.2179251

DescTools::Kurt(cautionfatigue$EMO, method =2,conf.level =.99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics use
d as
## endpoints

##      kurt    lwr.ci    upr.ci
## 1.1718696 0.2535414 2.4113716
```

```
#Transform
cautionfatigue$EMOsqt<-(cautionfatigue$EMO+1)^0.5
DescTools::Skew(cautionfatigue$EMOsqt, method =2,conf.level =.99)

##        skew      lwr.ci      upr.ci
##  0.45615215 -0.01437932  0.86173209

DescTools::Kurt(cautionfatigue$EMOsqt, method =2,conf.level =.99)

##       kurt     lwr.ci     upr.ci
##  0.4788188 -0.2133831  1.3504093

cautionfatigue$EMOlg<-log10(cautionfatigue$EMO+1)
DescTools::Skew(cautionfatigue$EMOlg,method =2,conf.level =.99)

##       skew     lwr.ci     upr.ci
##  0.1347472 -0.3768841  0.5023563

DescTools::Kurt(cautionfatigue$EMOlg, method =2,conf.level =.99)

##       kurt     lwr.ci     upr.ci
##  0.1469011 -0.3713613  0.8019250

cautionfatigue$EMO<-cautionfatigue$EMOlg
```

Variable creation and data subsetting

```
dem<-subset(cautionfatigue, cautionfatigue$party == "Democrat")
rep<-subset(cautionfatigue, cautionfatigue$party == "Republican")
cautionfatigue$disgust<-cautionfatigue$demdis+cautionfatigue$repdis
see<-subset(cautionfatigue, cautionfatigue$party == "Democrat"|cautionf
atigue$party=="Republican")
see$party<-droplevels(see$party)
lib<-subset(cautionfatigue, cautionfatigue$POLID =="Liberal")
lib$POLID<-droplevels(lib$POLID)
con<-subset(cautionfatigue, cautionfatigue$POLID == "Conservative")
con$POLID<-droplevels(con$POLID)
uncout<-subset(cautionfatigue, cautionfatigue$Cert_Cond == "Certainty"|
cautionfatigue$Cert_Cond == "Uncertainty")
uncout$Cert_Cond<-droplevels(uncout$Cert_Cond)
table(uncout$Cert_Cond)

##
## Uncertainty   Certainty
##          69          49

look<-subset(cautionfatigue, cautionfatigue$VACCINE == "No")
look$VACCINE<-droplevels(look$VACCINE)
```

Data Exclusion Criteria

```
mean(cautionfatigue$timing)

## [1] 1096.156
```

```
sd(cautionfatigue$timing)

## [1] 615.1713

boxplot(cautionfatigue$timing)
```

Sample Descriptives

```
mean(cautionfatigue$age)

## [1] 34.65984

sd(cautionfatigue$age)

## [1] 11.62741

table(cautionfatigue$ethnicity)

##
##                African American/Black                      Asian Ameri
can
##                                    23
18
##                 Asian Indian American             Click to write Choic
e 9
##                                    89
1
```

```
## Native Hawaiian or Pacific Islander                              Ot
her
##                                  12
1
##                      White American
##                                 100
```

```r
table(cautionfatigue$Education)
```

```
##
##          2 year degree         4 year degree             Doctorate
##                     17                   117                     3
##   High school graduate Less than high school   Professional degree
##                     14                     2                    55
##           Some college
##                     36
```

```r
table(cautionfatigue$gender)
```

```
##
##         Female   Male
##      1     99    144
```

```r
table(cautionfatigue$party)
```

```
##
##                                    Democrat
```

```
##                                               106
##                                             Green
##                                                 3
## I am not affiliated with a political party.
##                                                23
##                                       Independent
##                                                48
##                                        Republican
##                                                64

   table(cautionfatigue$County.Travel)

   ##
##       No Yes
##   4 143  97

   table(cautionfatigue$State.Travel)

   ##
##  No Yes
## 134 110

   table(cautionfatigue$County.Travel)

   ##
##       No Yes
##   4 143  97
```

```
table(cautionfatigue$VACCINE)

##
##  No Yes
## 159  85

table(cautionfatigue$Vaccine.intent)

##
##
##                                          1
## I have already received the COVID vaccine
##                                         38
##                                         No
##                                         54
##                                        Yes
##                                        151

table(cautionfatigue$POLID)

##
## Conservative      Liberal
##           78          166

table(list(cautionfatigue$VACCINE, cautionfatigue$POLID))
```

```
##      .2
## .1    Conservative Liberal
##   No            51     108
##   Yes           27      58
```

```
table(list(cautionfatigue$Vaccine.intent, cautionfatigue$POLID))
```

```
##                                             .2
## .1                                          Conservative Liberal
##                                                        1       0
##   I have already received the COVID vaccine            9      29
##   No                                                  24      30
##   Yes                                                 44     107
```

Prime Efficacy

```
table(cautionfatigue$Cert_Cond)
```

```
##
## Uncertainty   Certainty     Neutral
##          69          49         126
```

```
tapply(cautionfatigue$unc, cautionfatigue$Cert_Cond, var)
```

```
## Uncertainty   Certainty     Neutral
##   0.5458088   0.3944217   0.3394420
```

```
prime<-aov(cautionfatigue$unc~cautionfatigue$Cert_Cond)
bartlett.test(cautionfatigue$unc~cautionfatigue$Cert_Cond)

##
##  Bartlett test of homogeneity of variances
##
## data:  cautionfatigue$unc by cautionfatigue$Cert_Cond
## Bartlett's K-squared = 5.1643, df = 2, p-value = 0.07561

rstatix::welch_anova_test(cautionfatigue, formula = unc~Cert_Cond)

## # A tibble: 1 x 7
##   .y.       n statistic   DFn   DFd     p method
## * <chr> <int>     <dbl> <dbl> <dbl> <dbl> <chr>
## 1 unc     244      3.81     2  111. 0.025 Welch ANOVA

lsr::etaSquared(prime)

##                              eta.sq eta.sq.part
## cautionfatigue$Cert_Cond 0.03236656  0.03236656

TukeyHSD(prime)

##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = cautionfatigue$unc ~ cautionfatigue$Cert_Cond)
```

```
##
## $`cautionfatigue$Cert_Cond`
##                                 diff         lwr        upr     p adj
## Certainty-Uncertainty  0.33397097  0.05234354 0.61559840 0.0153573
## Neutral-Uncertainty    0.09854146 -0.12722739 0.32431031 0.5590949
## Neutral-Certainty     -0.23542951 -0.48922987 0.01837086 0.0753412
```

Confound Check

```
t.test(cautionfatigue$groupid~cautionfatigue$POLID)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$groupid by cautionfatigue$POLID
## t = 1.1992, df = 130.23, p-value = 0.2326
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.06845628  0.27917931
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   7.005715                   6.900354

rstatix::welch_anova_test(cautionfatigue, formula = groupid~party)

## # A tibble: 1 x 7
##   .y.         n statistic   DFn   DFd     p method
```

```
## * <chr>   <int>     <dbl> <dbl> <dbl> <dbl> <chr>
## 1 groupid   244      0.32     4  16.4 0.863 Welch ANOVA

eta<-aov(cautionfatigue$groupid~cautionfatigue$party)
lsr::etaSquared(eta)

##                           eta.sq eta.sq.part
## cautionfatigue$party 0.003362589 0.003362589

t.test(cautionfatigue$risk~cautionfatigue$VACCINE)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$risk by cautionfatigue$VACCINE
## t = 2.7989, df = 219.54, p-value = 0.005585
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.4487519 2.5849144
## sample estimates:
##  mean in group No mean in group Yes
##          15.98742          14.47059

lsr::cohensD(cautionfatigue$risk~cautionfatigue$VACCINE)

## [1] 0.3426917
```

```
t.test(cautionfatigue$EMO~cautionfatigue$VACCINE)
```

```
##
## 	Welch Two Sample t-test
##
## data:  cautionfatigue$EMO by cautionfatigue$VACCINE
## t = -2.8799, df = 180.66, p-value = 0.004459
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.05465158 -0.01021087
## sample estimates:
##  mean in group No mean in group Yes
##          1.539540          1.571971
```

```
lsr::cohensD(cautionfatigue$EMO~cautionfatigue$VACCINE)
```

```
## [1] 0.3801062
```

Differences in Perceived Emotion Between Masked and Unmasked Faces

```
library(tidyverse)
```

```
## ── Attaching packages ─────────────────────────────────────── tidyvers
e 1.3.0 ──
```

```
## ✓ tibble  3.1.0     ✓ purrr   0.3.4
## ✓ tidyr   1.1.3     ✓ stringr 1.4.0
## ✓ readr   1.3.1     ✓ forcats 0.4.0

## ── Conflicts ──────────────────────────────────── tidyverse_conflicts() ──
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x dplyr::recode() masks car::recode()
## x purrr::some()   masks car::some()
```

```
l1f<-data.frame(cautionfatigue$ME, cautionfatigue$UME)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "Mask", value = "Affect", -id )


library(ggplot2)
lines <- ggplot(long1f, aes(Mask, Affect))
lines + stat_summary(fun.y = mean, geom="bar")+
  labs(title = "Perceived Affect of Faces by Mask Status") +theme_classic()+
```

```
scale_x_discrete(labels = c("cautionfatigue.ME" = "Masked",
                              "cautionfatigue.UME" = "Unmasked"))

## Warning: `fun.y` is deprecated. Use `fun` instead.
```

Hypothesis 1

```
library(lavaan)

## This is lavaan 0.6-8
## lavaan is FREE software! Please report any bugs.

library(processR)

## This version of bslib is designed to work with shiny version 1.5.
0.9007 or higher.

##
## Attaching package: 'processR'

## The following objects are masked from 'package:car':
##
##     densityPlot, qqPlot
```

```r
library(MPsychoR)
labels = list(X="unc", M="SCM", Y="risk")
pmacroModel(4, labels = labels)
```

```r
model=tripleEquation(labels=labels)
cat(model)

## SCM~a*unc
## risk~c*unc+b*SCM
## indirect :=(a)*(b)
## direct :=c
## total := direct + indirect
## prop.mediated := indirect / total

semfit= sem(model = model, data = cautionfatigue, se = "boot", boots
trap=10)
summary(semfit, ci=TRUE)

## lavaan 0.6-8 ended normally after 37 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                         5
##
```

```
##   Number of observations                           244
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as
endpoints
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points

## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points

## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points

   ##
## Parameter Estimates:
##
##   Standard errors                              Bootstrap
##   Number of requested bootstrap draws                 10
##   Number of successful bootstrap draws                10
##
## Regressions:
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##   SCM ~
##     unc        (a)   13.610    4.384    3.104    0.002    5.154   21
.210
##   risk ~
```

```
##     unc        (c)    1.291    0.488    2.645    0.008    0.897    2
.503
##     SCM        (b)    0.018    0.004    4.230    0.000    0.009    0
.025
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##    .SCM            1816.303  203.626    8.920    0.000 1597.602 2196
.447
##    .risk             18.420    1.338   13.768    0.000   15.478   20
.193
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     indirect          0.238    0.117    2.041    0.041    0.096    0
.440
##     direct            1.291    0.515    2.509    0.012    0.897    2
.503
##     total             1.530    0.497    3.080    0.002    1.117    2
.759
```

```
##     prop.mediated     0.156     0.082     1.901     0.057     0.042     0
.329

reg<-lm(SCM~unc+groupid, data = cautionfatigue)
summary(reg)

##
## Call:
## lm(formula = SCM ~ unc + groupid, data = cautionfatigue)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -140.871  -20.076   -0.327   18.077  163.391
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   53.557     32.667   1.639 0.102420
## unc            9.895      4.286   2.309 0.021809 *
## groupid       15.907      4.602   3.456 0.000647 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 41.86 on 241 degrees of freedom
## Multiple R-squared:  0.08611,    Adjusted R-squared:  0.07852
## F-statistic: 11.35 on 2 and 241 DF,  p-value: 1.941e-05
```

```
QuantPsyc::lm.beta(reg)

##       unc   groupid
## 0.1468605 0.2198691

mult<-lm(risk~unc+EMO+covidbel, data = look)
summary(mult)

##
## Call:
## lm(formula = risk ~ unc + EMO + covidbel, data = look)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.2912  -2.7188   0.3328   2.3591  10.4815
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 17.70371    6.81228   2.599   0.0103 *
## unc          1.12325    0.47722   2.354   0.0198 *
## EMO         -9.81779    3.92300  -2.503   0.0134 *
## covidbel     0.19910    0.03555   5.601 9.49e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 4.251 on 155 degrees of freedom
## Multiple R-squared:  0.2416, Adjusted R-squared:  0.227
## F-statistic: 16.46 on 3 and 155 DF,  p-value: 2.45e-09
```

```
QuantPsyc::lm.beta(mult)
```

```
##       unc        EMO   covidbel
##  0.1666971 -0.1766748  0.3938900
```

Hypothesis 2

```
labels = list(X="groupid", M="SCM", Y="risk")
pmacroModel(4, labels = labels)
```

```
model=tripleEquation(labels=labels)
cat(model)
```

```
## SCM~a*groupid
## risk~c*groupid+b*SCM
## indirect :=(a)*(b)
## direct :=c
## total := direct + indirect
## prop.mediated := indirect / total
```

```
semfit= sem(model = model, data = look, se = "boot", bootstrap=10)
summary(semfit, ci=TRUE)
```

```
## lavaan 0.6-8 ended normally after 36 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                         5
##
##   Number of observations                           159
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as
endpoints
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
```

```
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points

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points

## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points

   ##
## Parameter Estimates:
##
##   Standard errors                             Bootstrap
##   Number of requested bootstrap draws                10
##   Number of successful bootstrap draws               10
##
## Regressions:
```

```
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##   SCM ~
##     groupid    (a)   14.407    5.305    2.716    0.007    4.023   21
.637
##   risk ~
##     groupid    (c)    1.682    0.720    2.336    0.019    0.442    2
.644
##     SCM        (b)    0.007    0.010    0.720    0.471   -0.007    0
.028
##
## Variances:
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##    .SCM              2049.290  249.296    8.220    0.000 1938.481 2811
.795
##    .risk               21.789    1.771   12.306    0.000   17.795   24
.821
##
## Defined Parameters:
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     indirect          0.107    0.157    0.683    0.495   -0.075    0
```

```
.401
##      direct           1.682    0.759    2.216    0.027    0.442    2
.644
##      total            1.789    0.746    2.398    0.016    0.447    2
.796
##      prop.mediated    0.060    0.135    0.445    0.657   -0.030    0
.421
```

Hypothesis 3

```
   #unmasked disgust by political leaning of face and participant
library(tidyverse)
pre<-data.frame(cautionfatigue$POLID, cautionfatigue$demdis, cautionfat
igue$repdis)
id<-1:nrow(pre)
pre<-cbind(id=id, pre)
hyp3<-gather(pre, key = "Political ID",value = "Disgust", -cautionfatig
ue.POLID, -id)
hyp3$face[hyp3$`Political ID` == "cautionfatigue.demdis"]<-"Dem Disgust
"
hyp3$face[hyp3$`Political ID` == "cautionfatigue.repdis"]<- "Rep Disgus
t"
head(hyp3)
```

```
##   id cautionfatigue.POLID          Political ID Disgust        fa
ce
## 1  1              Liberal cautionfatigue.demdis      61 Dem Disgust
## 2  2              Liberal cautionfatigue.demdis      66 Dem Disgust
## 3  3              Liberal cautionfatigue.demdis      62 Dem Disgust
## 4  4              Liberal cautionfatigue.demdis      55 Dem Disgust
## 5  5              Liberal cautionfatigue.demdis      61 Dem Disgust
## 6  6              Liberal cautionfatigue.demdis      71 Dem Disgust
```

```
#LMM for above mixed design
#Fixed Effects
library(nlme)
```

```
##
## Attaching package: 'nlme'
```

```
## The following object is masked from 'package:dplyr':
##
##     collapse
```

```
m1 <- lme(Disgust~face,random=~1|id,data=hyp3, method = "ML")
m2<- lme(Disgust~1, random = ~1|id,data=hyp3, method = "ML")
anova(m1, m2)
```

```
##     Model df      AIC      BIC    logLik   Test  L.Ratio p-value
## m1      1  4 3565.724 3582.485 -1778.862
## m2      2  3 3566.426 3578.997 -1780.213 1 vs 2 2.702111  0.1002

#Random Effects
m1 <- lme(Disgust~face,random=~1|cautionfatigue.POLID,data=hyp3, method
= "ML")
m2<- lme(Disgust~1, random = ~1|cautionfatigue.POLID,data=hyp3, method
= "ML")
anova(m1, m2)

##     Model df      AIC      BIC    logLik   Test  L.Ratio p-value
## m1      1  4 3601.424 3618.185 -1796.712
## m2      2  3 3601.136 3613.706 -1797.568 1 vs 2 1.711681  0.1908

l1f<-data.frame(cautionfatigue$MDDIST, cautionfatigue$MRDIST, cautio
nfatigue$UMDDIST, cautionfatigue$UMRDIST)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "Distance", -id )
head(long1f)

##   id                    ID Distance
## 1  1 cautionfatigue.MDDIST       17
## 2  2 cautionfatigue.MDDIST       12
```

```
## 3   3 cautionfatigue.MDDIST       14
## 4   4 cautionfatigue.MDDIST       12
## 5   5 cautionfatigue.MDDIST       10
## 6   6 cautionfatigue.MDDIST       11
```

```
#Distance by Mask Status and Political Affiliation
library(nlme)
model1<-lme(Distance~ID, random = ~1|id/ID, data=long1f,method="ML")
model1_baseline<-lme(Distance~1, random = ~1|id/ID, data=long1f,method=
"ML")
anova(model1_baseline,model1)
```

```
##                   Model df      AIC      BIC    logLik   Test  L.Ra
tio
## model1_baseline     1  4 4578.501 4598.035 -2285.250
## model1              2  7 4556.383 4590.568 -2271.192 1 vs 2 28.11749
##                 p-value
## model1_baseline
## model1           <.0001
```

```
pairwise.t.test(long1f$Distance,long1f$ID,paired=TRUE,p.adjust.metho
d="bonferroni")
```

```
##
##  Pairwise comparisons using paired t tests
##
```

```
## data:  long1f$Distance and long1f$ID
##
##                          cautionfatigue.MDDIST cautionfatigue.MRDIST
## cautionfatigue.MRDIST  0.9178                -
## cautionfatigue.UMDDIST 0.3801                0.0227
## cautionfatigue.UMRDIST 0.0052                6.4e-06
##                          cautionfatigue.UMDDIST
## cautionfatigue.MRDIST  -
## cautionfatigue.UMDDIST -
## cautionfatigue.UMRDIST 0.3217
##
## P value adjustment method: bonferroni
```

```
library(ggplot2)
lines <- ggplot(long1f, aes(ID, Distance, group=1))
lines + stat_summary(fun = mean, geom="line")+
  scale_x_discrete(labels = c("cautionfatigue.MDDIST" = "Masked Democra
t",
                              "cautionfatigue.MRDIST" = "Masked Republi
can",
                              "cautionfatigue.UMDDIST" = "Unmasked Demo
crat",
                              "cautionfatigue.UMRDIST" = "Unmasked Repu
blican")) +
```

```
  labs(title = "Distance by Mask Status and Political Affiliation") +th
eme_classic()+
  xlab("")
```

```
#General affect by mask status and political party of perceived face
.

l1f<-data.frame(cautionfatigue$MDSCM, cautionfatigue$MRSCM, cautionfati
gue$UMDSCM, cautionfatigue$UMRSCM)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "SCM", -id )
head(long1f)
```

```
##   id                    ID SCM
## 1  1 cautionfatigue.MDSCM  54
## 2  2 cautionfatigue.MDSCM  63
## 3  3 cautionfatigue.MDSCM  58
## 4  4 cautionfatigue.MDSCM  47
## 5  5 cautionfatigue.MDSCM  54
## 6  6 cautionfatigue.MDSCM  60
```

```
#LMM
library(nlme)
model1<-lme(SCM~ID, random = ~1|id, data=long1f,method="ML")
model1_baseline<-lme(SCM~1, random = ~1|id, data=long1f,method="ML")
anova(model1_baseline,model1)
```

```
##                 Model df      AIC      BIC    logLik   Test  L.Ra
tio
## model1_baseline     1  3 7175.973 7190.623 -3584.986
## model1              2  6 7164.743 7194.044 -3576.371 1 vs 2 17.22985
##                p-value
## model1_baseline
## model1           6e-04
```

```
pairwise.t.test(long1f$SCM,long1f$ID,paired=TRUE,p.adjust.method="bo
nferroni")
```

```
##
##  Pairwise comparisons using paired t tests
##
## data:  long1f$SCM and long1f$ID
##
##                        cautionfatigue.MDSCM cautionfatigue.MRSCM
## cautionfatigue.MRSCM  0.509                -
## cautionfatigue.UMDSCM 0.001                0.257
```

```
## cautionfatigue.UMRSCM 1.000                1.000

##                       cautionfatigue.UMDSCM

## cautionfatigue.MRSCM  -

## cautionfatigue.UMDSCM -

## cautionfatigue.UMRSCM 0.013

##

## P value adjustment method: bonferroni
```

```
library(ggplot2)

lines <- ggplot(long1f, aes(ID, SCM, group=1))

lines + stat_summary(fun = mean, geom="line")+

  scale_x_discrete(labels = c("cautionfatigue.MDSCM" = "Masked Democrat
",

                             "cautionfatigue.MRSCM" = "Masked Republica
n",

                             "cautionfatigue.UMDSCM" = "Unmasked Democr
at",

                             "cautionfatigue.UMRSCM" = "Unmasked Republ
ican")) +

  labs(title = "Stereotype Content by Mask Status and Political Affilia
tion") +theme_classic()+

  xlab("")
```

```
#Stereotype content by ethnicity with political leaning as covariate
.
l1f<-data.frame(cautionfatigue$HFSCM, cautionfatigue$WFSCM, cautionfati
gue$AFSCM,
                cautionfatigue$HMSCM, cautionfatigue$BMSCM, cautionfati
gue$AMSCM,
                cautionfatigue$WMSCM, cautionfatigue$BFSCM)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "SCM", -id )
head(long1f)
```

```
##   id                     ID SCM
## 1  1 cautionfatigue.HFSCM  42
## 2  2 cautionfatigue.HFSCM  31
## 3  3 cautionfatigue.HFSCM  28
## 4  4 cautionfatigue.HFSCM  20
## 5  5 cautionfatigue.HFSCM  28
## 6  6 cautionfatigue.HFSCM  32
```

```
#Fixed Effects
library(nlme)
model1<-lme(SCM~ID, random = ~1|id, data=long1f,method="ML")
```

```
model1_baseline<-lme(SCM~1, random = ~1|id, data=long1f,method="ML")
anova(model1_baseline,model1)

   ##                   Model df      AIC      BIC    logLik   Test L.Rat
io
## model1_baseline     1  3 12495.73 12512.46 -6244.865
## model1              2 10 12449.90 12505.66 -6214.948 1 vs 2  59.833
##                  p-value
## model1_baseline
## model1            <.0001

   #Random Effects
l1f<-data.frame(cautionfatigue$HFSCM, cautionfatigue$WFSCM, cautionfati
gue$AFSCM,
                cautionfatigue$HMSCM, cautionfatigue$BMSCM, cautionfati
gue$AMSCM,
                cautionfatigue$WMSCM, cautionfatigue$BFSCM, cautionfati
gue$POLID)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "SCM", -id, -cautionfatigue.POL
ID )
long1f$Identification<-long1f$cautionfatigue.POLID
```

```
library(nlme)
m1 <- lme(SCM~ID,random=~1|Identification,data=long1f, method = "ML")
m2<- lme(SCM~1, random = ~1|Identification,data=long1f, method = "ML")
anova(m1, m2)

   ##     Model df      AIC      BIC    logLik   Test  L.Ratio p-value
## m1      1 10 13280.82 13336.59 -6630.412
## m2      2  3 13296.76 13313.49 -6645.380 1 vs 2 29.93622   1e-04

   library(ggplot2)
lines <- ggplot(long1f, aes(ID, SCM, group=Identification, color=Identi
fication))
lines + stat_summary(fun = mean, geom="line")+
  scale_x_discrete(labels = c("cautionfatigue.AFSCM" = "Asian Female",
                              "cautionfatigue.AMSCM" = "Asian Male",
                              "cautionfatigue.BFSCM" = "Black Female",
                              "cautionfatigue.BMSCM" = "Black Male",
                              "cautionfatigue.HFSCM" = "Hispanic Female
",
                              "cautionfatigue.HMSCM" = "Hispanic Male",
                              "cautionfatigue.WFSCM" = "White Female",
                              "cautionfatigue.WMSCM" = "White Male")) +
  labs(title = "Perceived General Affect by Face Ethnicity") +theme_cla
ssic()+
  xlab("")+ ylab("Affect")
```

```
#Test of Comparisons by Political ID
l1f<-data.frame(con$HFSCM, con$WFSCM, con$AFSCM, con$HMSCM, con$BMSCM,
con$AMSCM,
                con$WMSCM, con$BFSCM)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "SCM", -id)

pairwise.t.test(long1f$SCM,long1f$ID,paired=TRUE,p.adjust.method="bonfe
rroni")

##
##  Pairwise comparisons using paired t tests
##
## data:  long1f$SCM and long1f$ID
##
##           con.AFSCM con.AMSCM con.BFSCM con.BMSCM con.HFSCM con.HMSC
M
## con.AMSCM -         -         -         -         -         -
## con.BFSCM 0.0087    0.0087    -         -         -         -
## con.BMSCM 1.0000    1.0000    0.2562    -         -         -
## con.HFSCM 1.0000    1.0000    0.3389    1.0000    -         -
## con.HMSCM 0.0492    0.0492    1.0000    1.0000    1.0000    -
```

```
## con.WFSCM 1.0000    1.0000    0.1335    1.0000    1.0000    0.6970

## con.WMSCM 1.0000    1.0000    0.5722    1.0000    1.0000    1.0000

##           con.WFSCM

## con.AMSCM -

## con.BFSCM -

## con.BMSCM -

## con.HFSCM -

## con.HMSCM -

## con.WFSCM -

## con.WMSCM 1.0000

##

## P value adjustment method: bonferroni
```

```
   l1f<-data.frame(lib$HFSCM, lib$WFSCM, lib$AFSCM, lib$HMSCM, lib$BMSC
M, lib$AMSCM,
                lib$WMSCM, lib$BFSCM)
l1f<-na.omit(l1f)
id<-1:nrow(l1f)
l1f<-cbind(id=id, l1f)
long1f<-gather(l1f, key = "ID", value = "SCM", -id)


pairwise.t.test(long1f$SCM,long1f$ID,paired=TRUE,p.adjust.method="bonfe
rroni")
```

```
##
##  Pairwise comparisons using paired t tests
##
## data:  long1f$SCM and long1f$ID
##
##           lib.AFSCM lib.AMSCM lib.BFSCM lib.BMSCM lib.HFSCM lib.HMSC
M
## lib.AMSCM -         -         -         -         -         -
## lib.BFSCM 1.3e-05   1.3e-05   -         -         -         -
## lib.BMSCM 1.0000    1.0000    0.0035    -         -         -
## lib.HFSCM 1.0000    1.0000    0.0093    1.0000    -         -
## lib.HMSCM 1.0000    1.0000    0.0085    1.0000    1.0000    -
## lib.WFSCM 1.0000    1.0000    1.4e-05   1.0000    1.0000    1.0000
## lib.WMSCM 1.0000    1.0000    0.1199    1.0000    1.0000    1.0000
##           lib.WFSCM
## lib.AMSCM -
## lib.BFSCM -
## lib.BMSCM -
## lib.HFSCM -
## lib.HMSCM -
## lib.WFSCM -
## lib.WMSCM 1.0000
```

```
##
## P value adjustment method: bonferroni

#Differences within each condition
t.test(cautionfatigue$AFSCM~cautionfatigue$POLID)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$AFSCM by cautionfatigue$POLID
## t = -0.18543, df = 146.21, p-value = 0.8532
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -2.268994  1.879745
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   24.76923                   24.96386

t.test(cautionfatigue$AMSCM~cautionfatigue$POLID)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$AMSCM by cautionfatigue$POLID
## t = -0.18543, df = 146.21, p-value = 0.8532
## alternative hypothesis: true difference in means is not equal to 0
```

```
## 95 percent confidence interval:
##  -2.268994  1.879745
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   24.76923                   24.96386

t.test(cautionfatigue$BFSCM~cautionfatigue$POLID)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$BFSCM by cautionfatigue$POLID
## t = 0.83691, df = 130.06, p-value = 0.4042
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.202515  2.965877
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   28.43590                   27.55422

t.test(cautionfatigue$BMSCM~cautionfatigue$POLID)

##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$BMSCM by cautionfatigue$POLID
```

```
## t = 0.43722, df = 156.22, p-value = 0.6626
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.522001  2.387308
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   25.78205                   25.34940
```

```
t.test(cautionfatigue$HFSCM~cautionfatigue$POLID)
```

```
##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$HFSCM by cautionfatigue$POLID
## t = -0.078864, df = 128.29, p-value = 0.9373
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -2.256696  2.083696
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                    25.5641                    25.6506
```

```
t.test(cautionfatigue$HMSCM~cautionfatigue$POLID)
```

```
##
##  Welch Two Sample t-test
```

```
##
## data:  cautionfatigue$HMSCM by cautionfatigue$POLID
## t = 1.9782, df = 116.25, p-value = 0.05027
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.002468555  4.147355796
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   27.60256                   25.53012
```

```
t.test(cautionfatigue$WFSCM~cautionfatigue$POLID)
```

```
##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$WFSCM by cautionfatigue$POLID
## t = 0.76225, df = 126.35, p-value = 0.4473
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.269713  2.860693
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   25.70513                   24.90964
```

```
t.test(cautionfatigue$WMSCM~cautionfatigue$POLID)
```

```
##
##  Welch Two Sample t-test
##
## data:  cautionfatigue$WMSCM by cautionfatigue$POLID
## t = -0.027986, df = 135.86, p-value = 0.9777
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -2.003523  1.947607
## sample estimates:
## mean in group Conservative      mean in group Liberal
##                   25.93590                   25.96386
```

Hypothesis 4

```
library(lavaan)
library(processR)
library(MPsychoR)
labels = list(X="groupid", M="disgust", Y="risk",W="unc")
pmacroModel(7, labels = labels)
```

```
moderator=list(name = "unc", site=list("a"))
model=tripleEquation(labels=labels, moderator = moderator)
cat(model)
```

```
## disgust~a1*groupid+a2*unc+a3*groupid:unc
## risk~c*groupid+b*disgust
## unc ~ unc.mean*1
## unc ~~ unc.var*unc
## CE.XonM :=a1+a3*unc.mean
## indirect :=(a1+a3*unc.mean)*(b)
## index.mod.med :=a3*b
## direct :=c
## total := direct + indirect
## prop.mediated := indirect / total
## CE.XonM.below :=a1+a3*(unc.mean-sqrt(unc.var))
## indirect.below :=(a1+a3*(unc.mean-sqrt(unc.var)))*(b)
## CE.XonM.above :=a1+a3*(unc.mean+sqrt(unc.var))
## indirect.above :=(a1+a3*(unc.mean+sqrt(unc.var)))*(b)
## direct.below:=c
## direct.above:=c
## total.below := direct.below + indirect.below
## total.above := direct.above + indirect.above
## prop.mediated.below := indirect.below / total.below
## prop.mediated.above := indirect.above / total.above

semfit= sem(model = model, data = look, se = "boot", bootstrap=10)

## Warning in lav_partable_vnames(FLAT, "ov.x", warn = TRUE): lavaan
WARNING:
```

```
##     model syntax contains variance/covariance/intercept formulas
##     involving (an) exogenous variable(s): [unc]; These variables wil
l
##     now be treated as random introducing additional free parameters.
##     If you wish to treat those variables as fixed, remove these
##     formulas from the model syntax. Otherwise, consider adding the
##     fixed.x = FALSE option.
```

```
## Warning in lav_model_vcov(lavmodel = lavmodel, lavsamplestats = l
avsamplestats, : lavaan WARNING:
##     The variance-covariance matrix of the estimated parameters (vcov
)
##     does not appear to be positive definite! The smallest eigenvalue
##     (= -1.272893e-15) is smaller than zero. This may be a symptom th
at
##     the model is not identified.
```

```
summary(semfit, ci=TRUE)
```

```
## lavaan 0.6-8 ended normally after 59 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        11
##
```

```
##   Number of observations                               159
##
## Model Test User Model:
##
##   Test statistic                                   650.242
##   Degrees of freedom                                     4
##   P-value (Chi-square)                               0.000
```

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as
endpoints

## Warning in FUN(newX[, i], ...): extreme order statistics used as
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## Warning in FUN(newX[, i], ...): extreme order statistics used as end
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## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points

## Warning in FUN(newX[, i], ...): extreme order statistics used as end
points
   ##
## Parameter Estimates:
##
##   Standard errors                             Bootstrap
##   Number of requested bootstrap draws                10
##   Number of successful bootstrap draws               10
```

```
##
## Regressions:
##                     Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##   disgust ~
##     groupid   (a1)   10.534   14.352    0.734    0.463  -15.970   27
.375
##     unc       (a2)   14.791   23.658    0.625    0.532  -28.409   45
.492
##     groupd:nc (a3)   -1.293    3.414   -0.379    0.705   -5.366    5
.003
##   risk ~
##     groupid    (c)    0.972    0.696    1.395    0.163   -0.068    1
.996
##     disgust    (b)    0.126    0.014    8.808    0.000    0.107    0
.151
##
## Intercepts:
##                     Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     unc     (unc.)    4.289    0.068   63.354    0.000    4.105    4
.347
##    .disgust          28.136   98.573    0.285    0.775  -98.972  205
```

```
.433
##    .risk             -6.587    4.163   -1.583    0.114  -14.689   -2
.262
##
## Variances:
##                       Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     unc     (unc.)     0.512    0.082    6.207    0.000    0.373    0
.675
##    .disgust          263.812   29.449    8.958    0.000  203.396  305
.893
##    .risk              17.442    1.468   11.881    0.000   15.057   20
.243
##
## Defined Parameters:
##                       Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     CE.XonM            4.989    1.953    2.555    0.011    1.000    8
.382
##     indirect           0.628    0.313    2.003    0.045    0.123    1
.230
##     index.mod.med     -0.163    0.464   -0.351    0.726   -0.627    0
.698
```

```
## 	direct 	0.972 	0.734 	1.324 	0.186 	-0.068 	1
.996
## 	total 	1.599 	0.500 	3.196 	0.001 	1.040 	2
.481
## 	prop.mediated 	0.392 	0.316 	1.242 	0.214 	0.061 	1
.059
## 	CE.XonM.below 	5.914 	2.784 	2.124 	0.034 	1.573 	8
.931
## 	indirect.below 	0.744 	0.405 	1.838 	0.066 	0.193 	1
.353
## 	CE.XonM.above 	4.064 	3.679 	1.105 	0.269 	-0.708 	9
.585
## 	indirect.above 	0.511 	0.508 	1.006 	0.314 	-0.087 	1
.338
## 	direct.below 	0.972 	0.734 	1.324 	0.186 	-0.068 	1
.996
## 	direct.above 	0.972 	0.734 	1.324 	0.186 	-0.068 	1
.996
## 	total.below 	1.715 	0.646 	2.657 	0.008 	1.072 	2
.959
## 	total.above 	1.483 	0.557 	2.664 	0.008 	0.617 	2
.244
## 	prop.medtd.blw 	0.434 	0.321 	1.351 	0.177 	0.147 	1
```

```
.064
##     prop.meditd.bv    0.345    0.354    0.973    0.330   -0.048    1
.054
```

Hypothesis 5

```
library(lavaan)
library(processR)
library(MPsychoR)
labels = list(X="combelief", M="EMO", Y="risk",W="unc")
pmacroModel(7, labels = labels)
```

```
moderator=list(name = "unc", site=list("a"))
model=tripleEquation(labels=labels, moderator = moderator)
cat(model)

## EMO~a1*combelief+a2*unc+a3*combelief:unc
## risk~c*combelief+b*EMO
## unc ~ unc.mean*1
## unc ~~ unc.var*unc
## CE.XonM :=a1+a3*unc.mean
## indirect :=(a1+a3*unc.mean)*(b)
## index.mod.med :=a3*b
## direct :=c
## total := direct + indirect
```

```
## prop.mediated := indirect / total
## CE.XonM.below :=a1+a3*(unc.mean-sqrt(unc.var))
## indirect.below :=(a1+a3*(unc.mean-sqrt(unc.var)))*(b)
## CE.XonM.above :=a1+a3*(unc.mean+sqrt(unc.var))
## indirect.above :=(a1+a3*(unc.mean+sqrt(unc.var)))*(b)
## direct.below:=c
## direct.above:=c
## total.below := direct.below + indirect.below
## total.above := direct.above + indirect.above
## prop.mediated.below := indirect.below / total.below
## prop.mediated.above := indirect.above / total.above
```

```
semfit= sem(model = model, data = look, se = "boot", bootstrap=10)
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cl
uster, :
## lavaan WARNING: some observed variances are (at least) a factor 1000
times
## larger than others; use varTable(fit) to investigate
```

```
## Warning in lav_partable_vnames(FLAT, "ov.x", warn = TRUE): lavaan
WARNING:
##     model syntax contains variance/covariance/intercept formulas
##     involving (an) exogenous variable(s): [unc]; These variables wil
l
```

```
##     now be treated as random introducing additional free parameters.
##     If you wish to treat those variables as fixed, remove these
##     formulas from the model syntax. Otherwise, consider adding the
##     fixed.x = FALSE option.
```

```
## Warning in lav_model_vcov(lavmodel = lavmodel, lavsamplestats = l
avsamplestats, : lavaan WARNING:
##     The variance-covariance matrix of the estimated parameters (vcov
)
##     does not appear to be positive definite! The smallest eigenvalue
##     (= -9.882111e-16) is smaller than zero. This may be a symptom th
at
##     the model is not identified.
```

```
summary(semfit, ci=TRUE)
```

```
## lavaan 0.6-8 ended normally after 53 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        11
##
##   Number of observations                           159
##
## Model Test User Model:
```

```
##
##   Test statistic                                679.803
##   Degrees of freedom                                  4
##   P-value (Chi-square)                            0.000
```

Warning in FUN(newX[, i], ...): extreme order statistics used as endpoints

Warning in FUN(newX[, i], ...): extreme order statistics used as endpoints

```
## Warning in FUN(newX[, i], ...): extreme order statistics used as end
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points

   ##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws               10
##   Number of successful bootstrap draws              10
##
## Regressions:
##                     Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
```

```
pper
##   EMO ~
##     combelief (a1)    0.001    0.014    0.097    0.923   -0.019    0
.021
##     unc       (a2)   -0.002    0.116   -0.018    0.986   -0.167    0
.159
##     comblf:nc (a3)   -0.000    0.003   -0.123    0.902   -0.005    0
.004
##   risk ~
##     combelief  (c)    0.087    0.080    1.093    0.274    0.006    0
.246
##     EMO        (b)  -12.020    5.015   -2.397    0.017  -20.886   -2
.408
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u
pper
##     unc     (unc.)    4.289    0.052   83.104    0.000    4.163    4
.343
##    .EMO               1.561    0.490    3.184    0.001    0.924    2
.310
##    .risk             31.690    7.886    4.018    0.000   18.090   46
.810
```

```
##

## Variances:

##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u

pper

##      unc     (unc.)    0.512    0.076    6.720    0.000    0.328    0

.635

##     .EMO                0.007    0.001   13.794    0.000    0.006    0

.008

##     .risk              21.972    1.744   12.601    0.000   16.667   22

.836

##

## Defined Parameters:

##                      Estimate  Std.Err  z-value  P(>|z|) ci.lower ci.u

pper

##      CE.XonM          -0.000    0.002   -0.218    0.827   -0.003    0

.002

##      indirect          0.005    0.028    0.166    0.868   -0.038    0

.055

##      index.mod.med     0.005    0.051    0.098    0.922   -0.047    0

.113

##      direct            0.087    0.084    1.037    0.300    0.006    0

.246

##      total             0.092    0.071    1.285    0.199    0.021    0
```

```
.207
## prop.mediated 0.051 0.312 0.165 0.869 -0.185 0
.747
## CE.XonM.below -0.000 0.003 -0.035 0.972 -0.005 0
.004
## indirect.below 0.001 0.039 0.030 0.976 -0.034 0
.086
## CE.XonM.above -0.001 0.003 -0.203 0.839 -0.006 0
.004
## indirect.above 0.008 0.053 0.156 0.876 -0.072 0
.131
## direct.below 0.087 0.084 1.037 0.300 0.006 0
.246
## direct.above 0.087 0.084 1.037 0.300 0.006 0
.246
## total.below 0.088 0.089 0.995 0.320 -0.000 0
.241
## total.above 0.095 0.071 1.346 0.178 -0.010 0
.211
## prop.medtd.blw 0.013 1561.373 0.000 1.000 -8.025 4936
.744
## prop.meditd.bv 0.087 0.591 0.146 0.884 -0.417 1
.589
```