A Longitudinal Study on the Effects of Discrimination, Internalized Homophobia, and Stigmatization on Measures of Well-being for LGBQ Individuals

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Contents

Introduction

Health is something that is on everyone's mind these days, especially due to the circumstances of the past two years. However, even with health being a hot topic in the past few years, one key aspect of our health often falls by the wayside: mental health. Perhaps it's due to the difficulty in diagnosis or its particularly cryptic nature, but mental health has always been an afterthought for all of us, even though it has become more important than ever. The past few years we have been living through particularly tumultuous chapters of history, and stress levels just continue to rise higher and higher (Bethune, 2022).

Even so, we still see a lot of stigma regarding mental health even today. Over half (56%) of adults with a mental disorder don't receive help (Access to Care Data, 2022), often choosing to avoid treatment due to worrying about being treated differently and getting judged. Perhaps they are right to be concerned, considering how insults like retarded, autistic, psychopathic, mental, etc. are still so common. It is often easy to forget what the original meaning of these words are when we have become so used to seeing them be hurled around as insults. It can be extremely intimidating to let others know about your mental health issues, or even just your inner feelings.

We see many similarities with those who are LGBTQ+. Just as someone may choose to avoid disclosing their mental health issues, many in the LGBTQ+ community choose to "stay in the closet." Many of them internalize the hate and homophobia around them, believing that they are "wrong" and not being able to accept themselves. Various studies have shown that those who are homophobic are more likely to have repressed homosexual desires (Adams et al., 1996; Cheval et al., 2016; Weinstein et al., 2012).

These ideas led us to our general idea for a research question: How does discrimination affect the mental health of those who identify as LGBTQ+? Past research has looked at vaguely similar questions. For example, there have been many studies about LGB status and mental health issues, reporting a high association. However, these studies do not typically consider discrimination. There have also been many studies about mental health discrimination and LGBQT+ discrimination, but very few that look at the overall combination. Among these few studies, there are none that we have found that are longitudinal in design, which we believe will provide many advantages. For example, a longitudinal study allows for seeing how a change in discrimination variables may change overall mental health, and is not affected by differences between individuals (such as sexual orientation, gender, ethnicity, race, age, religion, physical appearance, income level/social class, etc.)

Dataset Description

As we looked for datasets related to our ideas, we found one called "Project STRIDE." This was a three-year research project conducted in New York that collected data on the effect of stress and minority identity related to sexual orientation, race/ethnicity and gender on mental health (Meyer et al., 2018). The study used a longitudinal design with measures at baseline and after a one-year follow-up. Baseline interviewing began in February 2004 and was completed in January 2005. To find respondents, the researchers went to various venues and asked people to participate. Snowball sampling was also conducted, where respondents were encouraged to invite others to participate as well.

Most of the score variables within the data were calculated by taking the answers to the questions related to that variable, standardizing the results, and taking the average. Many of the questions allowed an answer from an ordinal scale of agreement with choices ranging from "strongly agree" to "strongly disagree". For all of the variables, a higher score reflected higher or more, i.e. more discrimination, or higher levels of well-being. The researchers collecting this data did not appear to have statistical or mathematical background, and the overall purpose of the study was the data collection itself rather than analysis of the data collected.

The resulting dataset from the project had 524 respondents and 944 variables (around half of these are variables for the one-year followup). These variables included various demographic characteristics such as gender, age, race/ethnicity, sexual orientation, employment status, relationship status, and education. The dataset also included multiple variables regarding discrimination denoted as stigmatization, internalized homophobia, and everyday discrimination. These were the predictor variables that we decided we wanted to look at in particular. Lastly, a few other variables that stood out were related to mental health, which we wanted to look at as an outcome. The key mental health variables we found during our exploratory analysis and after trying some models were personal well-being, social well-being, and psychological guilt. The following brief descriptions for variables were provided by the study (Meyer et al., 2018). For more information regarding these variables, how they were calculated, and how the data was collected, we encourage taking a closer look at this source.

Discrimination Predictor Variables

Stigma (STIGMA) is a variable in the data that was calculated based on a scale for assessing expectations of rejection and discrimination. An example of a question which contributed to this score was, "Most people would willingly accept someone like me as a close friend," with responses from a scale of agreement.

Internalized homophobia (IHP) is a variable which assessed the extent to which a respondent did not accept their sexual orientation, were uneasy about their desires towards the same-sex, and seeked to repress their feelings. An example if a question which contributed to this score is "How often have you wished you weren't gay?".

Everyday discrimination (DIS) measured routine and sometimes subtle experiences of unfair treatment. Examples include being treated with less respect than others, receiving worse service than others, and being threatened, harassed, or insulted. Questions were asked about how often these experiences occurred, and what the discrimination was related to (i.e. sexual orientation, gender, ethnicity, race, age, religion, appearance, income, social class, or otherwise).

Mental Health Variables

Personal well-being (PERWELLB) is a measure of psychological well-being and life course development. Contributing to this score were 18 statements that were about self-acceptance, positive relations with others, autonomy, environmental mastery, personal growth, and life purpose (3 each), with responses from a scale of agreement. Some examples include: "When I look at the story of my life I am pleased with how things have turned out", "In general, I feel I am in charge of the situation in which I live" and "For me, life has been a continuous process of learning, changing, and growth".

Social well-being (SOCWELLB) is a measure of social well-being, examining respondents' perception of their social environment and society. This score was calculated with 15 statements related to social-acceptance, social actualization, social contribution, social coherence, and social integration (3 each) with responses from a scale of agreement. Some examples are "Society has stopped making progress," and "I have nothing important to contribute to society."

Psychological guilt (PERI-G) assesses psychological distress in the domain of guilt, whether rational or irrational. The score was calculated using the 4 question Psychiatric Epidemiology Research Interview (PERI) scale. Thus, this variable is typically denoted as PERI Guilt Score. One question as an example is "How often have you felt guilty about the things you do or don't do?".

Collective self-esteem (COLSE) was measured using the collective self-esteem scale, and represents an individual's evaluation of their collective identity and group memberships. There were 16 questions about membership esteem, public collective self-esteem, private collective self-esteem, and importance to identity (4 each).

Support network score (SUPPORT) was a score that assessed social support for the individuals. Questions were asked that helped to identify the size of a respondents support network, the number of key supporters, the number of emotional supporters, and the type and coverage of support received.

Research Question

The variables of this dataset paved the path for a refined research question: How does stigmatization, internalized homophobia, and everyday discrimination affect the mental health measurements of psychological well-being, social well-being, and psychological guilt for those who identified as lesbian, gay, bisexual, or queer? If there is an association, what is its magnitude and what form does it take? (By form we mean questions of whether the association is longitudinal or cross-sectional in nature).

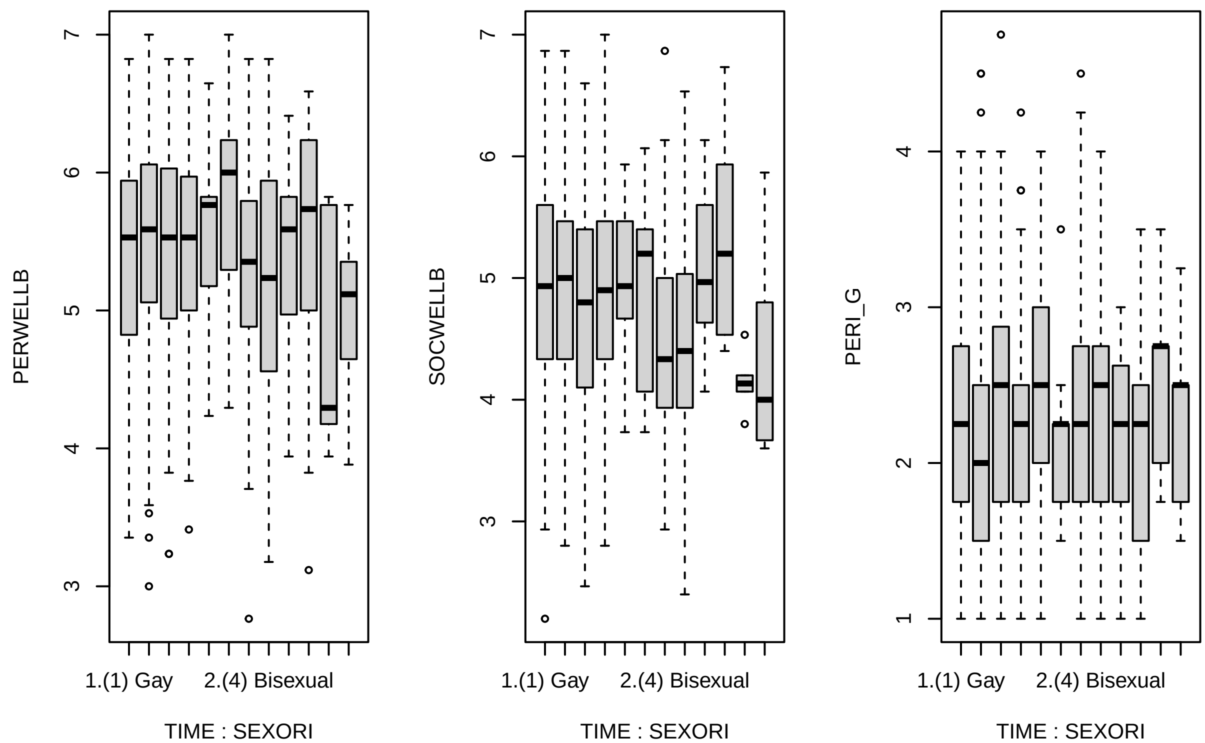
Exploratory Analysis

Pre-Processing

Since our research question was only relevant to individuals part of the non-heterosexual community, individuals in the original dataset who identified as straight or heterosexual were removed. This reduced the total number of participants in the study from 524 to 370. Interestingly enough, only individuals who identify as non-heterosexual were interviewed at follow-up, therefore having a research question centered around non-heterosexual individuals helped to eliminate a large portion of the missing observations.

Visualizing the Data

The box plots below are organized by when an outcome measurement was collected (year 1 vs. year 2) and the different sexual orientation groups (from left to right: Gay, Lesbian, Queer, Bisexual, Homosexual, Other-LGB).



From the box plots, we see that in general, regardless of an individual's sexual orientation, their psychological well-being and social well-being score tend to decrease after a one year follow-up while their PERI guilt score increases after a one year follow-up.

We observed the largest drops in psychological and social well-being scores in the "Homosexual" and "Other-LGB" groups. For PERI guilt scores, the largest increases are seen in the "Lesbian" and "Other-LGB" groups. However, we note that drastic changes in the "Other-LGB" could be coincidental since said group only contains five individuals.

The sets of longitudinal plots shown in the Appendix were constructed from a random sample of 50 individuals who were divided into groups based on their sexuality. We note that every collection of longitudinal plots is missing a plot for the "Other-LGB' ' group. This is probably due to the lack of individuals in the original dataset who fall within this group.

We also notice that in each set of longitudinal plots, there are no discernible dominant trends. For example, in the psychological well-being score plots there are just as many individuals who observe an increase or no change in their psychological well-being score as there are individuals who observe a decrease in score. We find similar observations for the other sets of plots. This suggests that an individual's sexuality is not an accurate predictor of an individual's mental health.

Therefore, despite non-heterosexual individuals being more likely than heterosexual individuals to suffer from mental health and substance abuse issues, worse mental health is not an inborn characteristic of non-heterosexual individuals. It is more likely that the trends seen in the mental health of non-heterosexual individuals are caused by external factors that relate to their sexual orientation; for example, the discrimination and stigmatization faced by non-heterosexual individuals surrounding their sexual orientation are likely to be a strong contributing factor to a reduction in mental health scores.

Methods

Model Overview

For each outcome we fit a linear mixed effects model with a random intercept for each individual and a random slope corresponding to the age of each individual. The age of each individual was included as a random factor due to the fact that if the study was repeated, the age variable would likely have a new random selection of ages. The covariates for age, ethnicity, gender, discrimination score, internalized homophobia score, collective self-esteem score, support network score, a bisexual indicator, and stigma score made up the fixed effects portion of the model. Age, discrimination score, internalized homophobia score, collective self-esteem score, support network score, and stigma score were given corresponding baseline covariates due to their time varying nature and the assumption that the baseline covariates are likely to have a cross-sectional effect on the outcomes (i.e. a higher baseline collective self-esteem score will likely result in better psychological well-being).

Variables contributing to an individual ethnicity, gender, and whether they identified as bisexual were fitted as well. The bisexual indicator variable was included as there is a small body of research that shows bisexual individuals can sometimes face discrimination and stigmatization from both the heterosexual and traditional LGBQ communities (Cruz, 2017).

Results

Complete Case Analysis

Due to there being a very low amount of missing data (less than 5% of the observations are incomplete), we first opt to conduct complete case analysis. Recall that the inferences made from complete case analysis can only be considered valid if the missing observations are missing completely at random, and the number of incomplete observations make up a small percentage of the total observations.

Table 1: Variables with Missing Data

Variables	DIS	IHP	PERWELLB	PERI_G	SOCWELLB	STIGMA	SUPPORT
Missing Obs Count	1	6	5	2	5	5	1

Psychological Well-Being

When using psychological well-being as the outcome we find that there is evidence that the cross-sectional and longitudinal effects of the covariates differ at the 5% significance level.

Table 2: Likelihood Ratio Test Results

Model	df	AIC	BIC	logLik	L.Ratio	p
Full model	21	1274.920	1370.732	-616.4601	-	-
Reduced model	15	1285.161	1353.597	-627.5803	22.24043	0.0011

Using $0.5\chi_1^2 + 0.5\chi_2^2$, we also find that the random slope is not statistically significant ($p = 0.9997$). Consequently, the random slope is removed from the model leaving the random intercept. The results from our final model are displayed below.

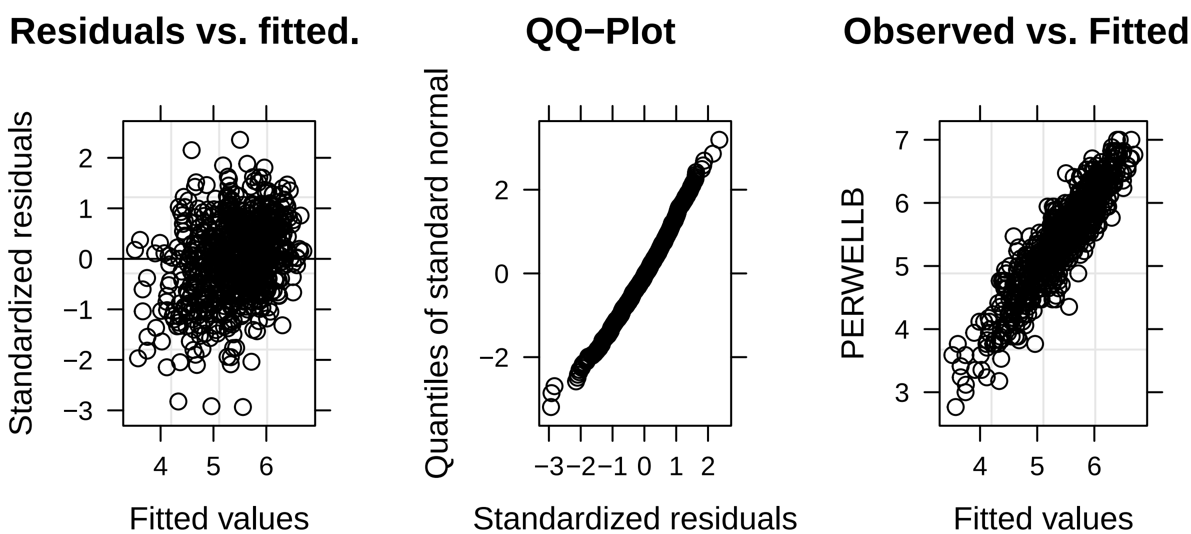
Table 3: Psychological Well-Being Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	-0.0019 (-0.0591, 0.0554)	0.0291	0.9487
	BASE_AGE	-0.0048 (-0.0622, 0.0527)	0.0292	0.8702
	ETHNIC: Black/African-American	0.1066 (-0.0552, 0.2683)	0.0823	0.196
	ETHNIC: Latino/Hispanic	0.0463 (-0.1190, 0.2117)	0.0841	0.5818
	GENDER: FEMALE	-0.0913 (-0.2178, 0.0352)	0.0643	0.1567
	DIS	-0.106 (-0.2046, -0.0074)	0.0501	0.0352
	BASE_DIS	-0.0928 (-0.2366, 0.0510)	0.0731	0.2052
	IHP	-0.2095 (-0.3769, -0.0420)	0.0852	0.0144
	BASE_IHP	-0.118 (-0.3073, 0.0713)	0.0962	0.221
	COLSE	0.1777 (0.1050, 0.2505)	0.037	0
	BASE_COLSE	0.15 (0.0570, 0.2429)	0.0473	0.0016
	SUPPORT	0.0068 (-0.0116, 0.0252)	0.0094	0.4673
	BASE_SUPPORT	0.0159 (-0.0096, 0.0413)	0.013	0.2202
	BISEXUAL	0.1104 (-0.0640, 0.2847)	0.0887	0.2139
	STIGMA	-0.0362 (-0.1307, 0.0583)	0.0481	0.4521
	BASE_STIGMA	-0.0661 (-0.1883, 0.0561)	0.0621	0.2884
Random	sd(Intercept | RID)	0.5109 (0.4609, 0.5664)		
	sd(Residual)	0.4105 (0.3808, 0.4427)		

From Table 3, we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on psychological well-being (while holding ethnicity, gender, and the bisexual indicator constant) are -0.0019, -0.106, -0.2095, 0.1777, 0.0068, and -0.0362 respectively. However, it is worth noting that only the longitudinal effects of discrimination score, internalized homophobia score, and collective self esteem score are statistically significant at the 5% significance level.

From the longitudinal effect of discrimination score we infer that for a unit increase in discrimination score, the psychological well-being score of an individual decreases by 0.106 for any given change in the other covariates over a single year interval. The longitudinal effects for internalized homophobia and collective self esteem scores have similar interpretations, with a unit increase in the collective self esteem score resulting in a 0.1777 increase in psychological well-being, and a unit increase in the internalized homophobia score resulting in a 0.2095 decrease in psychological well-being.

Table 3 also shows that the cross-sectional effects of baseline effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on psychological well-being are -0.0067, -0.1988, -0.3275, 0.3277, 0.0227, and -0.1023 respectively.



From the collection of plots above, we see that the normality assumption as well as the constant residual variance assumption are satisfied; the points on the QQ-plot approximately follow a straight line, while the standardized residuals in the residual plot appear to be randomly placed and evenly distributed about 0. From the Observed vs. Fitted plot we see a clear linear trend, indicating that the fitted model is able to predict the observed values of the psychological well-being scores relatively well.

Social Well-Being

For this particular model we only fit a random intercept, since a linear mixed effects model is unable to reach convergence if a random slope corresponding to the age of each individual is fit.

When using social well-being as the outcome, we find evidence that the cross-sectional and longitudinal effects of the covariates differ at the 5% significance level.

Table 4: Likelihood Ratio Test Results

Model	df	AIC	BIC	logLik	L.Ratio	p
Full model	19	1361.462	1448.149	-616.4601	-	-
Reduced model	12	1534.613	1589.362	-755.3063	187.1502	<0.0001

The results from our final model are displayed below.

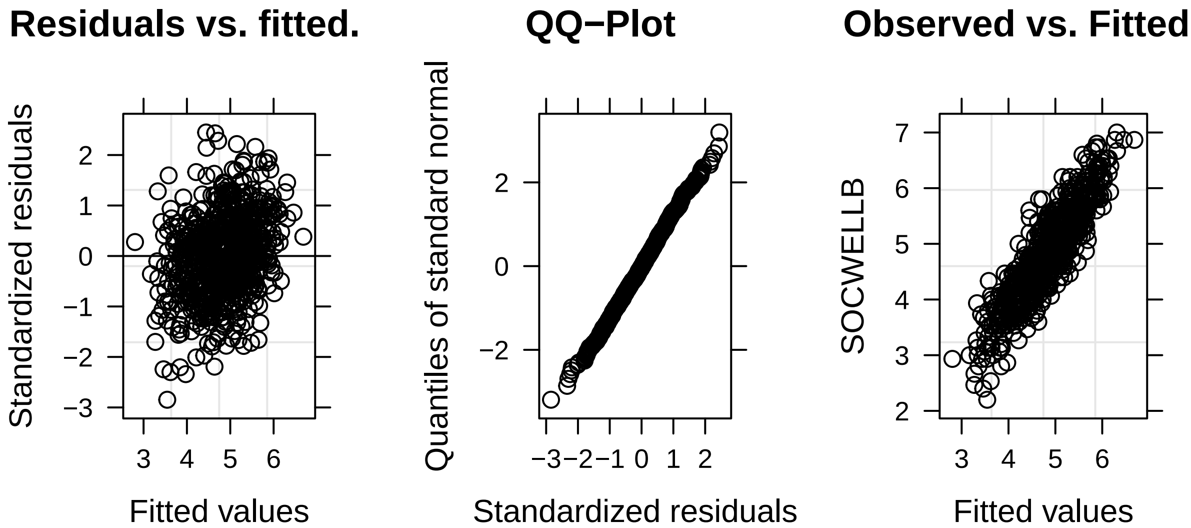
Table 5: Social Well-Being Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	-0.0522 (-0.1168, 0.0124)	0.0328	0.1127
	BASE_AGE	0.0581 (-0.0067, 0.1228)	0.0329	0.0786
	ETHNIC: Black/African-American	0.0571 (-0.1032, 0.2173)	0.0815	0.4839
	ETHNIC: Latino/Hispanic	0.0791 (-0.0847, 0.2428)	0.0833	0.3431
	GENDER: FEMALE	-0.205 (-0.3301, -0.0798)	0.0636	0.0014
	DIS	-0.0682 (-0.1790, 0.0425)	0.0563	0.2266
	BASE_DIS	-0.0658 (-0.2134, 0.0818)	0.0751	0.3813
	IHP	-0.1211 (-0.3091, 0.0669)	0.0956	0.206
	BASE_IHP	-0.0311 (-0.2319, 0.1697)	0.1021	0.7609
	COLSE	0.3726 (0.2909, 0.4543)	0.0415	0
	BASE_COLSE	0.128 (0.03147, 0.2245)	0.0491	0.0095
	SUPPORT	0.0059 (-0.0148, 0.0265)	0.0105	0.5768
	BASE_SUPPORT	0.0069 (-0.0193, 0.0330)	0.0133	0.6073
	BISEXUAL	-0.1374 (-0.3100, 0.0352)	0.0878	0.1184
	STIGMA	-0.0765 (-0.1828, 0.0298)	0.054	0.1577
	BASE_STIGMA	-0.0112 (-0.1374, 0.1150)	0.0642	0.8614
Random	sd(Intercept | RID)	0.4746 (0.4214, 0.5346)		
	sd(Residual)	0.4728 (0.4386, 0.5096)		

From Table 5, we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on social well-being (while holding ethnicity, gender, and the bisexual indicator constant) are -0.0522, -0.0682, -0.1211, 0.3726, 0.0059, and -0.0765 respectively. However, at the 5% significance level, only the longitudinal effect of the collective self esteem score is statistically significant.

From the longitudinal effect of collective self esteem score, we infer that for a unit increase in the collective self esteem score, the social well-being score of an individual increases by 0.3726 for any given change in the other covariates over a single year interval.

Table 5 also shows that the cross-sectional effects of baseline effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on social well-being are 0.0059, -0.134, -0.1522, 0.5006, 0.0128, and -0.0877 respectively.



From the group of plots shown above, we can reasonably conclude that the normality and constant residual variance assumption are satisfied in this model. In the Residual vs. Fitted plot we see that the standardized residuals are randomly scattered about 0, indicating that the residuals likely have a constant variance. In the QQ-plot, the points follow a straight line very closely, meaning that the normality assumption is a valid assumption to make for this model. Finally, in the Observed vs. Fitted plot we see a clear linear trend which suggests that this model is able to predict the observed social well-being scores relatively well.

PERI Guilt Score

When using PERI Guilt Score as the outcome, we find that there is evidence that the cross-sectional and longitudinal effects of the covariates differ at the 5% significance level.

Table 6: Likelihood Ratio Test Results

Model	df	AIC	BIC	logLik	L.Ratio	p
Full model	21	1339.040	1434.851	-648.5200	-	-
Reduced model	15	1344.551	1412.988	-657.2757	17.51136	0.0076

Using $0.5\chi_1^2 + 0.5\chi_2^2$, we also find that the random slope is not statistically significant ($p = 0.9998$). Consequently, the random slope is removed from the model leaving the random intercept. The results from our final model are displayed below.

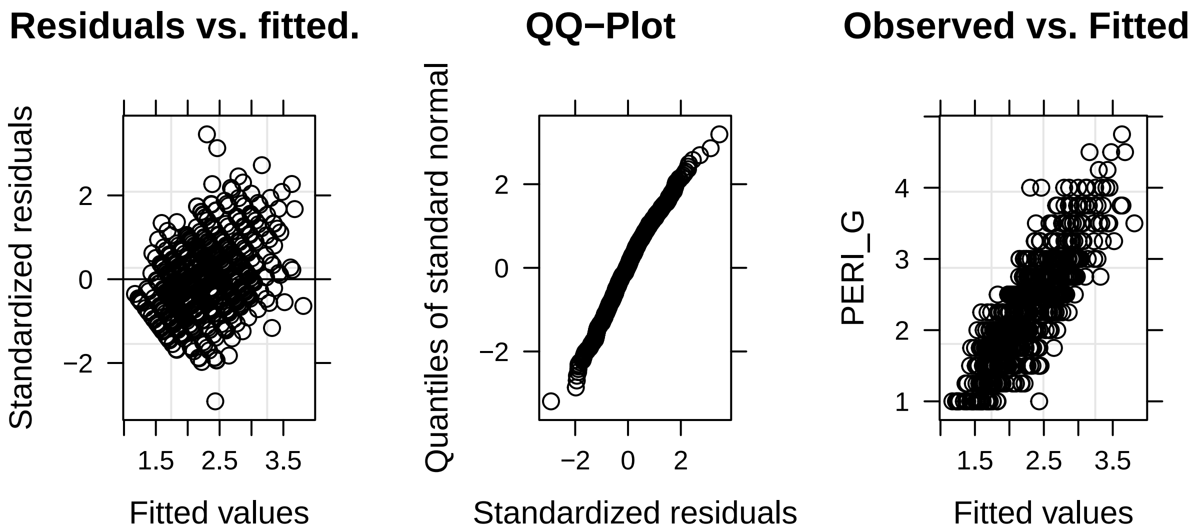
Table 7: PERI Guilt Score Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	0.0049 (-0.0609, 0.0707)	0.0335	0.8833
	BASE_AGE	-0.0124 (-0.0783, 0.0535)	0.0335	0.7117
	ETHNIC: Black/African-American	-0.2547 (-0.4037, -0.1057)	0.0758	9e-04
	ETHNIC: Latino/Hispanic	-0.1629 (-0.3152, -0.0107)	0.0774	0.0361
	GENDER: FEMALE	0.1036 (-0.0127, 0.2198)	0.0591	0.0806
	DIS	0.1201 (0.0076, 0.2325)	0.0572	0.0365
	BASE_DIS	0.2127 (0.0714, 0.3540)	0.0718	0.0033
	IHP	0.2861 (0.0953, 0.4769)	0.097	0.0034
	BASE_IHP	0.0843 (-0.1124, 0.2811)	0.1	0.3998
	COLSE	-0.0795 (-0.1624, 0.0034)	0.0422	0.0602
	BASE_COLSE	-0.017 (-0.1101, 0.0762)	0.0474	0.7201
	SUPPORT	0.0034 (-0.0176, 0.0243)	0.0107	0.7531
	BASE_SUPPORT	-0.0161 (-0.0412, 0.0090)	0.0128	0.207
	BISEXUAL	-0.1129 (-0.2733, 0.0475)	0.0816	0.1671
	STIGMA	0.0703 (-0.0377, 0.1784)	0.0549	0.2012
	BASE_STIGMA	0.0243 (-0.0970, 0.1457)	0.0617	0.6936
Random	sd(Intercept | RID)	0.4115 (0.3573, 0.4740)		
	sd(Residual)	0.4914 (0.4557, 0.5298)		

From Table 7, we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on psychological well-being (while holding ethnicity, gender, and the bisexual indicator constant) are 0.0049, 0.1201, 0.2861, -0.0795, 0.0034, and 0.0703 respectively. However, only the longitudinal effects of discrimination score and internalized homophobia score are statistically significant at the 5% significance level. The collective self-esteem score is close to being significant at the 5% significance level as its p value is around 0.06.

From the longitudinal effect of discrimination score we infer that for each unit increase in discrimination score, the PERI guilt score of an individual increases by 0.1201 for any given change in the other covariates over a single year interval. We also infer from the longitudinal effect for internalized homophobia score that a unit increase in an individual's internalized homophobia score will result in a 0.2861 increase in the PERI guilt score.

Table 7 also shows that the cross-sectional effects of baseline effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on psychological well-being are -0.0075, 0.3328, 0.3704, -0.0965, -0.0127, and 0.0946 respectively.



From the collection of plots above, we can see that in both the Residuals vs. Fitted plot and the Observed vs. Fitted plot that groups of points form patterns of straight lines. This is because the variable PERI guilt score only takes on the values 1, 1.25, 1.5,. . . ,4.75 within the dataset, i.e. values that are not multiples of 0.25 do not appear. This is due to the 4 question scale that the Project STRIDE researchers used to calculate the PERI guilt scores.

Taking this into account, we still see that the standardized residuals Residual vs. Fitted plot are randomly distributed around 0, while the Observed vs. Fitted plot generally displays a linear trend. Therefore, it may still be somewhat accurate to state that the constant variance assumption is satisfied and that the model performs fairly well at predicting the observed PERI guilt score values. The points in the QQ-plot roughly form a straight line, however upon closer examination of the plot we see that the line has a very slight curve in the middle. Consequently, we are unable to conclude with 100% certainty that the normality assumption is satisfied.

Available Data Analysis

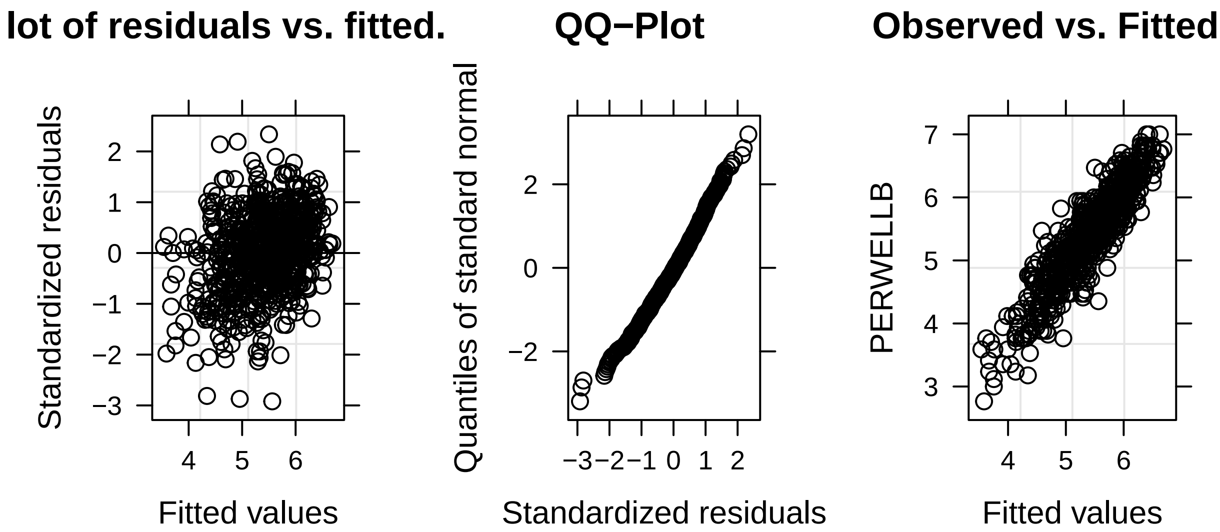
However complete case analysis may not be necessary when modeling with a linear mixed model. The way the `lmer` function in R fits a linear mixed model to a dataset that has missing observations is by removing observations with missing data which usually results in unbalanced longitudinal data. In general this is known as available data analysis, and if the missing data is missing at random, linear mixed models (a likelihood based technique) are able to accommodate the missingness. Therefore, for comparison purposes we will refit our final three models for psychological well-being, social well-being and PERI guilt scores without omitting incomplete cases.

Psychological Well-Being

Table 8: Psychological Well-Being Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	-0.003 (-0.0606, 0.0546)	0.0293	0.9183
	BASE_AGE	-0.0037 (-0.0615, 0.0541)	0.0294	0.8995
	ETHNIC: Black/African-American	0.1052 (-0.0546, 0.2651)	0.0813	0.1963
	ETHNIC: Latino/Hispanic	0.0497 (-0.1139, 0.2132)	0.0832	0.5506
	GENDER: FEMALE	-0.0997 (-0.2251, 0.0257)	0.0638	0.119
	DIS	-0.0937 (-0.1919, 0.0045)	0.0499	0.0615
	BASE_DIS	-0.1019 (-0.2447, 0.0409)	0.0726	0.1615
	IHP	-0.223 (-0.3910, -0.0550)	0.0854	0.0094
	BASE_IHP	-0.1051 (-0.2942, 0.0840)	0.0961	0.2751
	COLSE	0.1681 (0.0953, 0.2409)	0.037	0
	BASE_COLSE	0.1609 (0.0689, 0.2529)	0.0468	7e-04
	SUPPORT	0.0076 (-0.0109, 0.0262)	0.0094	0.4173
	BASE_SUPPORT	0.0168 (-0.0084, 0.04207)	0.0128	0.1911
	BISEXUAL	0.0985 (-0.0732, 0.27026)	0.0873	0.2598
	STIGMA	-0.0314 (-0.1257, 0.0630)	0.048	0.5136
	BASE_STIGMA	-0.0696 (-0.1914, 0.0521)	0.0619	0.2613
Random	sd(Intercept | RID)	0.5069 (0.4572, 0.5619)		
	sd(Residual)	0.4146 (0.3847, 0.4467)		

From Table 8, we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on psychological well-being (while holding ethnicity, gender, and the bisexual indicator constant) are -0.003, -0.0937, -0.223, 0.1681, 0.0076, -0.0314 respectively. This is relatively similar to the effects obtained from the complete case analysis, which were -0.0019, -0.106, -0.2095, 0.1777, 0.0068, and -0.0362. However the significance of the longitudinal effects has changed: the longitudinal effect of discrimination score is no longer statistically significant at the 5% significance level (the p-value is now 0.06).



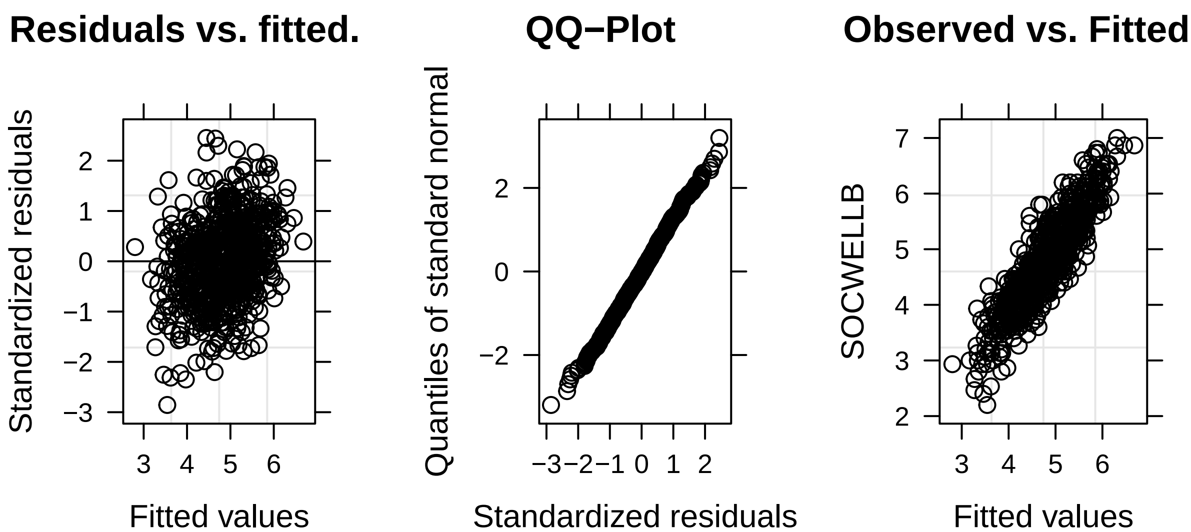
The collection of diagnostic plots above for the new model greatly resemble the diagnostic plots for the old complete case model; we see that the normality assumption as well as the constant residual variance assumption are satisfied and that the fitted model is able to predict the observed psychological well-being scores relatively well.

Social Well-Being

Table 9: Social Well-Being Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	-0.0519 (-0.1160, 0.0122)	0.0326	0.1121
	BASE_AGE	0.0577 (-0.0065, 0.1219)	0.0327	0.0781
	ETHNIC: Black/African-American	0.0611 (-0.0978, 0.2199)	0.0808	0.4502
	ETHNIC: Latino/Hispanic	0.0833 (-0.0791, 0.2457)	0.0826	0.3138
	GENDER: FEMALE	-0.2003 (-0.3242, -0.0763)	0.063	0.0016
	DIS	-0.0692 (-0.1789, 0.0405)	0.0558	0.2158
	BASE_DIS	-0.0682 (-0.2143, 0.0779)	0.0743	0.359
	IHP	-0.1218 (-0.3084, 0.0647)	0.0949	0.1999
	BASE_IHP	-0.03 (-0.2294, 0.1694)	0.1014	0.7672
	COLSE	0.3715 (0.2907, 0.4523)	0.0411	0
	BASE_COLSE	0.1292 (0.03409, 0.2244)	0.0484	0.0079
	SUPPORT	0.0054 (-0.0151, 0.0259)	0.0104	0.6049
	BASE_SUPPORT	0.0071 (-0.0188, 0.0330)	0.0132	0.5917
	BISEXUAL	-0.1344 (-0.3053, 0.0365)	0.0869	0.1229
	STIGMA	-0.0738 (-0.1786, 0.0309)	0.0533	0.1666
	BASE_STIGMA	-0.0161 (-0.1408, 0.1085)	0.0634	0.7995
Random	sd(Intercept | RID)	0.4728 (0.4200, 0.5323)		
	sd(Residual)	0.4706 (0.4368, 0.5070)		

Similar to what was observed with the psychological well-being models, from Table 9 we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on social well-being score (while holding ethnicity, gender, and the bisexual indicator constant) also did not change much. Additionally, similar to the previous pair of models, we find that the statistical significance of several variables has changed; at the 5% significance level, only the longitudinal effect of the collective self esteem score is statistically significant.



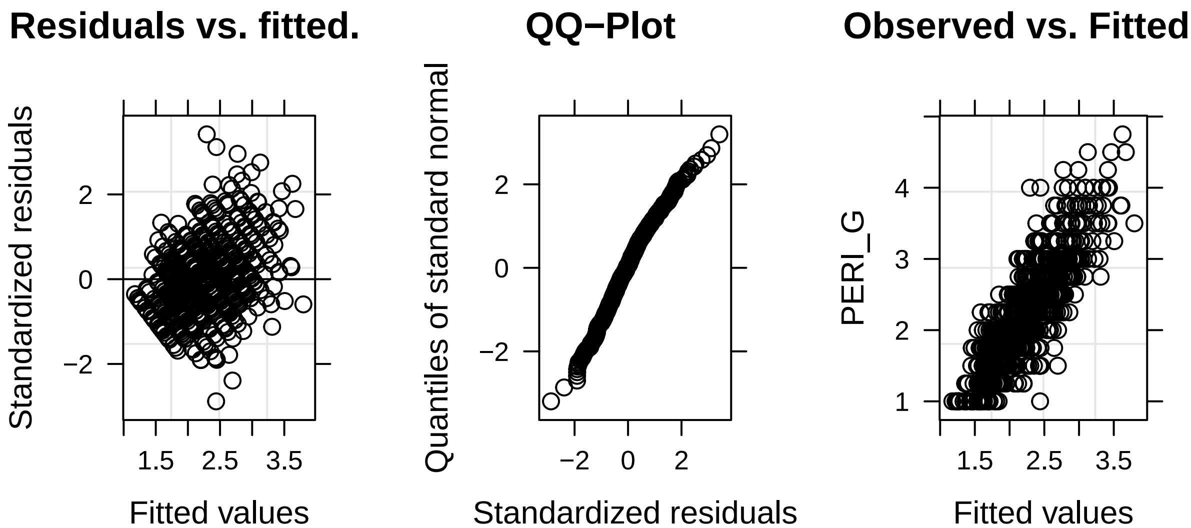
Again, from the group of plots shown above we can reasonably conclude that the normality and constant residual variance assumption are satisfied and that this model fits the observed data relatively well.

PERI Guilt Score

Table 10: PERI Guilt Score Model Results

Effect	Variables	Estimate (95% CI)	SE	p
Fixed	AGE	0.0052 (-0.0613, 0.0717)	0.0338	0.878
	BASE_AGE	-0.0122 (-0.0788, 0.0544)	0.0339	0.7193
	ETHNIC: Black/African-American	-0.2676 (-0.4151, -0.1201)	0.075	4e-04
	ETHNIC: Latino/Hispanic	-0.1792 (-0.3301, -0.0283)	0.0767	0.0201
	GENDER: FEMALE	0.0915 (-0.0238, 0.2068)	0.0586	0.1195
	DIS	0.1365 (0.0243, 0.2488)	0.0571	0.0173
	BASE_DIS	0.2165 (0.0762, 0.3568)	0.0714	0.0026
	IHP	0.2653 (0.0740, 0.4565)	0.0972	0.0067
	BASE_IHP	0.0939 (-0.1023, 0.2902)	0.0998	0.3472
	COLSE	-0.0753 (-0.1585, 0.0079)	0.0423	0.0763
	BASE_COLSE	-0.0261 (-0.1184, 0.0662)	0.047	0.5787
	SUPPORT	0.0018 (-0.0194, 0.0229)	0.0108	0.8702
	BASE_SUPPORT	-0.0149 (-0.0399, 0.0099)	0.0127	0.2393
	BISEXUAL	-0.1364 (-0.2942, 0.0213)	0.0802	0.0899
	STIGMA	0.0437 (-0.0635, 0.1510)	0.0545	0.4232
	BASE_STIGMA	0.0466 (-0.0737, 0.1668)	0.0611	0.4467
Random	sd(Intercept | RID)	0.4058 (0.3511, 0.4690)		
	sd(Residual)	0.4994 (0.4635, 0.5380)		

From Table 10 we see that the longitudinal effects of age, discrimination score, internalized homophobia score, collective self esteem score, support network score, and stigma score on the PERI guilt score (while holding ethnicity, gender, and the bisexual indicator constant) are similar to the previous complete case model's estimated effects. However, we note that the longitudinal effect of support network score and stigma score have noticeably decreased and increased respectively. Again, only the longitudinal effects of discrimination score and internalized homophobia score are statistically significant at the 5% significance level.



Similar patterns that were observed in the complete case model's diagnostic plots are also seen in this model's diagnostic plots; again we have difficulty concluding that the normality assumption is satisfied.

Discussion

General Conclusions

Psychological Well-being

On the population level, the level of discrimination, stigmitization, and internalized homophobia that a non-heterosexual individual experiences is negatively associated with their overall psychological well-being with high significance. This conclusion is intuitive, as all of these factors can cause intense psychological distress. Particularly, feelings of internalized homophobia can be increadibly damaging to a non-heterosexual individual struggling to come to terms with their sexual orientation.

Social Well-being

A non-heterosexual individual's collective self-esteem appears to be the strongest predictor of whether their social well-being scores are high or low. On the population level, we see that the higher a collective self-esteem score is, the higher the corresponding social well-being score tends to be. This observation is also intuitive; since an individual's social well-being score is measured by how connected and accepted they feel with society, it makes sense that this variable would share a strong correlation with collective self-esteem: the variable that measures how confident and self-assured one feels in the groups they identify with.

An interesting note is that being female also had a significant negative effect on an LGBQ individual's social well-being score. Perhaps this suggests that there are differences in how groups primarily involving females socially interact with each other in comparison to other genders.

PERI Guilt Score

At the population level, the discrimination and internalized homophobia an LGBQ individual experiences is negatively correlated with their PERI guilt score, similarly to what was found for the psychological well-being scores. This conclusion makes sense: the PERI guilt score functions as a measure of the amount of psychological distress an individual feels and centers around feelings of guilt. If an non-heterosexual individual is constantly being discriminated against and harbours negative feelings towards their own sexual orientation, it makes sense that they will start experiencing increased feelings of guilt towards themselves.

It is also worth noting that an individual's ethnicity had a significant negative effect on their PERI guilt score. Specifically, identifying as either African-American/Black or Latino/Hispanic resulted in decreased PERI guilt scores compared to individuals who identified as white.

Random Intercept

In each of the models, the estimated standard deviation of the random intercept is approximately 0.4 to 0.5, indicating that there is some respondent-to-respondent variability in the data.

Miscellaneous Observations

We found that being bisexual had a negative effect on an individual's psychological well-being score, social well-being score, and their PERI guiilt score. These effects were found to not be significant, suggesting that there is no significant difference between how bisexual individuals score compared to non-bisexual individuals.

Additionally, while a unit increase in the number of people in a non-heterosexual individual's social support group did have a positive longitudinal effect on said individual's psychological and social well-being scores and a negative effect on said individual's PERI guilt scores, the effects were found to be insignificant according to the dataset, suggesting that a large support network is not a "cure all" solution to an non-heterosexual individual's mental health issues.

Comparison of Complete Case and Available Data Analysis

In general, the estimated coefficients of the complete case analysis models and available data analysis models did not differ too much. This is likely because missing data make up a very small portion of overall dataset. The only noticeable differences between the two models was that certain variables became less significant in the available data analysis models. This is likely because by deleting incomplete cases from the dataset, we are reducing the overall sample size which results in a reduction in the efficiency of the estimators.

Limitations

We note that the dataset has a very specific population: non-heterosexual individuals from New York City (NYC) in 2004 to 2006. The dataset also only has 2 time points: a baseline measurement, and a follow-up after a year, and thus the analysis we can conduct with regards to a longitudinal effect is restricted. Due to the restricted scope of the data, it may be the case that the findings from the data do not generalize to a greater population, that is, LGBTQ+ individuals nationally or worldwide in the present time. This data was collected over 15 years ago, and many things have changed since then. One clear difference as an example is greater acceptance of LGBTQ+ individuals (at least in North America). For example, Canada legalized same-sex marriage in July of 2005 (Eichler et al., 2016), which was about half a year after the baseline data was finished collected for this dataset. The United States (where NYC is located and hence where the data was collected) took even longer to recognize same-sex marriage. This further shows how differences in location and country may prevent the generalization of our findings. In the present time, in the countries Iran and Saudia Arabia homosexuality is illegal and punishable by up to death (Bearak & Cameron, 2016). This dataset also did not acknowlege gender identity, i.e. those who identify as trangender, nonbinary, or otherwise. Although this is not really a limitation of our study, clearly discrimination affects the mental health of these individuals as well, and it would have been interesting to analyze these associations for gender identity.

With the STRIDE Project data, our study essentially takes the data as is, with the assumption that the questions are meaningful, and that the overall outcome scores are calculated properly and are relevant. However, these scores for discrimination and mental health are still subjective overall, as there are no perfect measurements for mental health like there would be for physical health (i.e. weight, hieght, number of tumours, etc.) The researchers collecting the STRIDE Project data have a background in political and social sciences rather than a statistical or mathematical background. This is beneficial in some ways, as it means that the questions being asked are relevant and meaningful. However, a lack of statistical and mathematical background may mean that there may be a better way to aggregate the answers or calculate the scores. For example, as previously stated in our dataset description, many ordinal categorical variables were collected as responses to questions and the researchers took an average of the questions for the score. However, it could be possible that a weighted average would be better for the variables, such that some questions may be more important than others. Another possibility is to use the individual answers to the questions rather than aggregating these variables through feature engineering, but this would create a lot more data and greatly decrease the interpretability of our model and results. If we cared more about prediction rather than interpretability, we could look at doing this and exploring other models designed for large scale datasets and better prediction (examples include random forests, gradient boosting, support vector machines, etc.), but that was not our goal for this study.

Further Research

It would be interesting to do similar research again on a national scale with more time points, using location as an additional predictor, and considering transgender and queer individuals. The inclusion of additional data collected over more time points would provide a lot more information to analyze that would also hopefully better generalize the results for the greater LGBTQ+ community. A few interesting ideas that can be explored with additional time points include seeing how discrimination evolves over time (i.e. Do we see more or less discrimination over time? What form does discrimination take over time? Do the reasons for discrimination change over time?), seeing how mental health scores vary over time through different events (such as recessions, disease outbreaks, and war), and better analyzing the longitudinal effects of discrimination on mental health.

Conclusion

Overall, the results show an obvious truth: Discrimination hurts. Discrimination has become widespread and institutinalized, to the point where many even internalize that hatred and prejudice. This is likely why people are often unwilling to share details about their lives and truths about themselves; they are worried about those who will judge and discriminate. Although we looked specifically at non-heterosexual indivuals, discrimination happens to everybody for many different reasons. When collecting the dataset, the researchers made sure to word the discrimination and stigma questions in a way such that it was not specifically about homophobia, but about stigma and discrimination in general. Even though we mentioned that the scope of data was fairly limited, it is very likely that the findings generalize not just those who identify as non-heterosexual, but to all people in general.

Similarly, we can extend internalized homophobia to the general acceptance of self and identity. For example, self-stigma is also seen in those with mental illness (Corrigan & Rao, 2012). We also see that to a lesser extent that many are often afraid of being "weird" or "quirky", lest they get ostracized. As we saw from our results, internalized homophobia is detrimental to mental health as a whole. Similarly, it is often said that self-acceptance is necessary for good mental health, or at the very least have numerous psychological benefits (Jimenez et al., 2010; Garcia et al., 2014; Shepard, 1979).

The world continues to become more stressful everyday. Amidst all these stressful global events, discrimination separates us when we should be working together. No matter the sexual orientation, gender, race, ethnicity, religion, or disability, people are people, and we are all in the same boat. As our lifetimes continue to be written into history books one world crisis at a time, it is more important now than ever to communicate with, accept, and care for one another.

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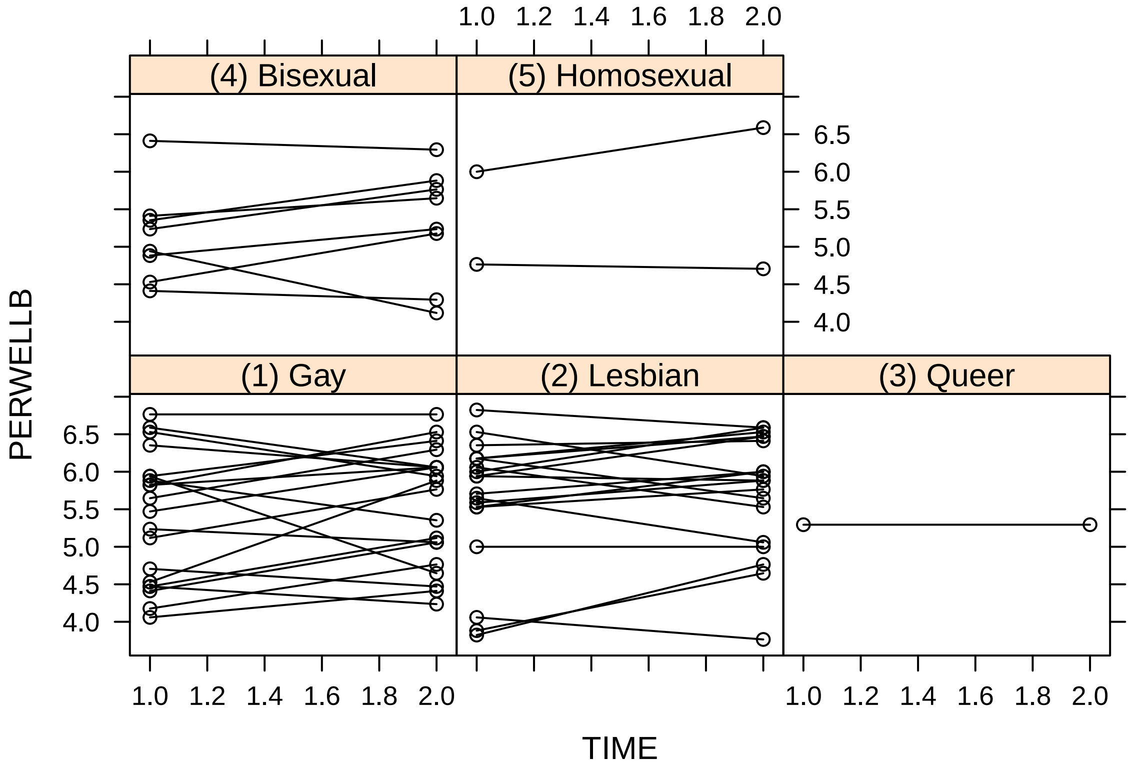
Appendix

Figures

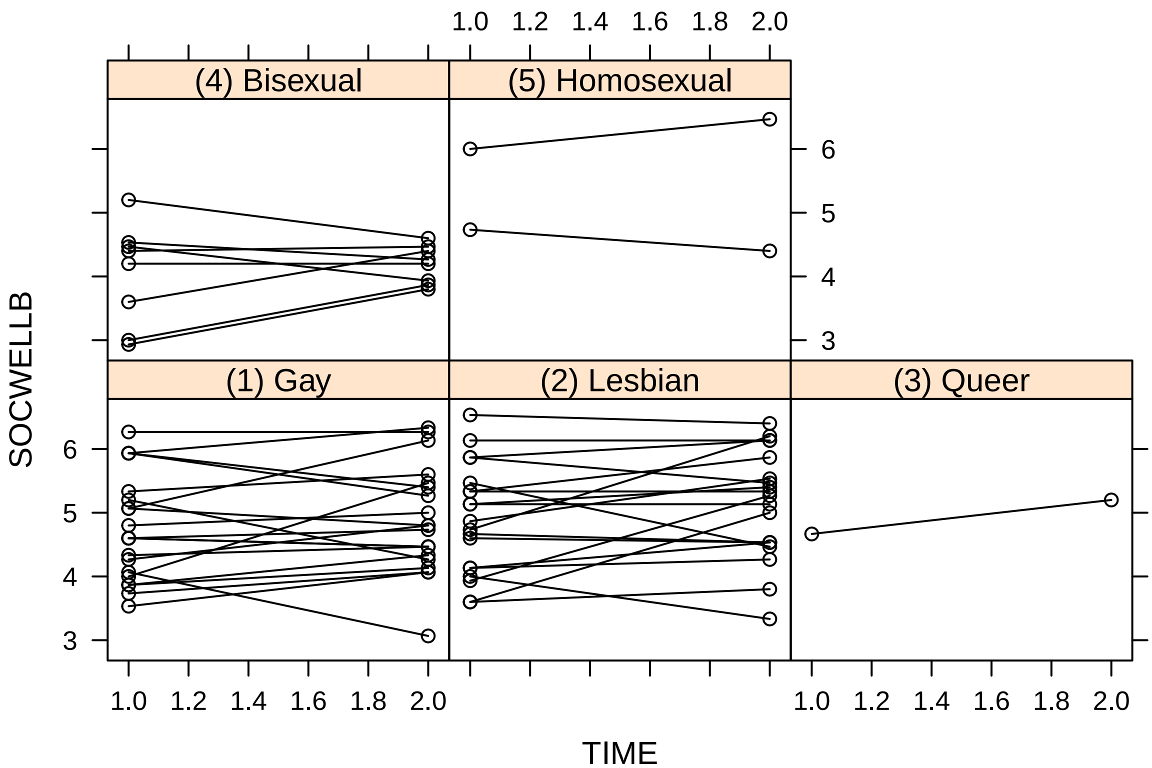
```
set.seed(437)
samp = sample(unique(newdata$RID),50)
randomdat = newdata[which(newdata$RID %in% samp),]
a = lattice::xyplot(PERWELLB ~ TIME |SEXORI,
                data = randomdat,
                groups = RID,
                col = 'black',
                type = c('l', 'p'))
b = lattice::xyplot(SOCWELLB ~ TIME |SEXORI,
                data = randomdat,
                groups = RID,
                col = 'black',
                type = c('l', 'p'))
c = lattice::xyplot(PERI_G ~ TIME|SEXORI ,
                data = randomdat,
                groups = RID,
                col = 'black',
                type = c('l', 'p'))

a
```

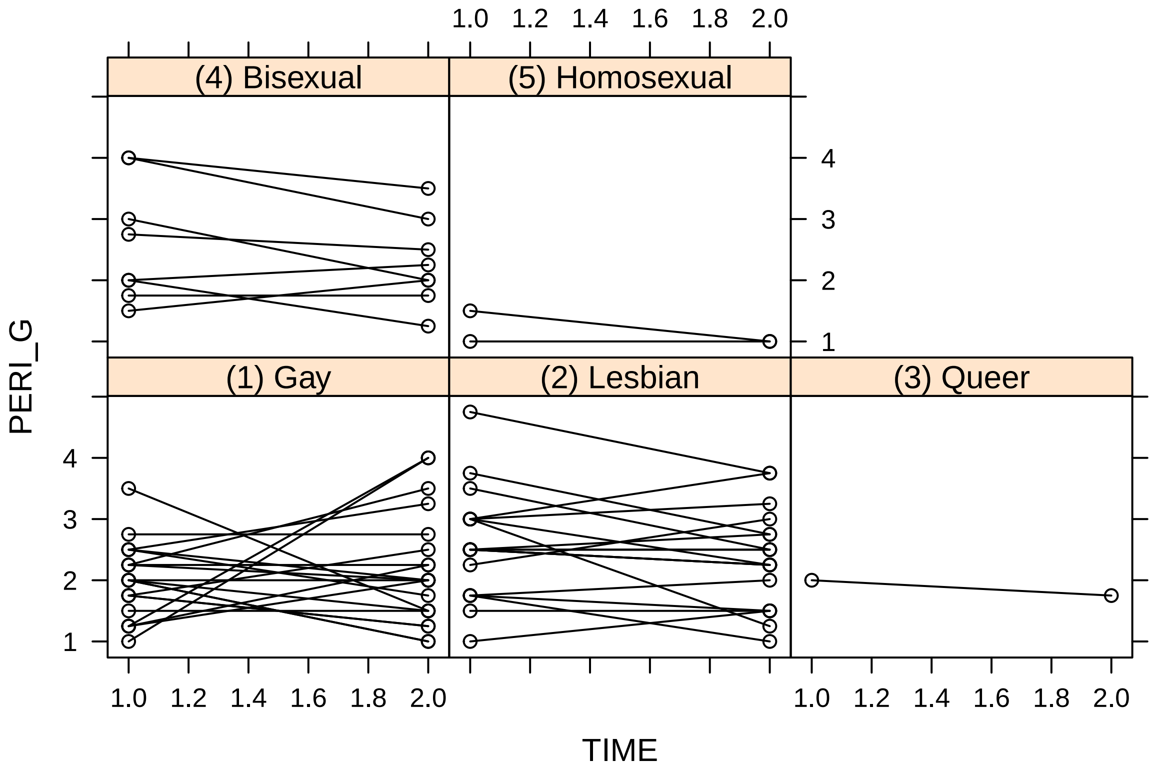


(4) Bisexual
(5) Homosexual
(1) Gay
(2) Lesbian
(3) Queer
PERWELLB
TIME
1.0 1.2 1.4 1.6 1.8 2.0
4.0 4.5 5.0 5.5 6.0 6.5


```
b
```


(4) Bisexual
(5) Homosexual
(1) Gay
(2) Lesbian
(3) Queer
SOCWELLB
TIME
1.0
1.2
1.4
1.6
1.8
2.0
3
4
5
6

c



R Code

```
knitr::opts_chunk$set(eval = FALSE, include = FALSE)
library(knitr)
library(kableExtra)
library(nlme)
library(gridExtra)
library(lattice)
library(mice)
library(lme4)
qmixchisq <- function(df1, df2, q) {
  sig_level <- 1 - q

  L_fn <- function(c) {
    computed_sig <- 0.5*pchisq(c, df1) + 0.5*pchisq(c, df2)
    (sig_level - computed_sig)^2
  }

  lower <- qchisq(sig_level, df1)
  upper <- qchisq(sig_level, df2)
```

```
  optimize(L_fn, interval=c(lower, upper))$minimum
}
pmixchisq <- function(df1, df2, W) {
  0.5*pchisq(W, df1) + 0.5*pchisq(W, df2)
}
load("C:/Users/lilyz/Downloads/35525-0001-Data.rda")
d =da35525.0001
d = d[!is.na(d$HAS_TIME2),]
n = nrow(d)

newdata = data.frame(RID = rep(d$RID, 2),
                     TIME = c(rep(1,370),rep(2,370)),
                     AGE = c(d$AGE, d$AGE_2),
                     BASE_AGE = rep(d$AGE, 2),
                     ETHNIC = rep(d$ETHNIC,2),
                     GEND = rep(d$GENDER,2),
                     DIS = c(d$DIS_TOT, d$DIS_TOT_2), ##
                     BASE_DIS = rep(d$DIS_TOT, 2),
                     IHP = c(d$IHP, d$IHP_2), ###
                     BASE_IHP = rep(d$IHP, 2), #############
                     COLSE = c(d$COLSE, d$COLSE_2),
                     BASE_COLSE = rep(d$COLSE,2),
                     PERWELLB = c(d$PERWELLB, d$PERWELLB_2), #########
                     BASE_PERWELLB = rep(d$PERWELLB, 2),
                     PERI_G = c(d$PERI_G, d$PERI_G_2), ##2
                     BASE_PERI_G = rep(d$PERI_G, 2), ## 4
                     SOCWELLB = c(d$SOCWELLB, d$SOCWELLB_2), ##
                     BASE_SOCWELLB = rep(d$SOCWELLB, 2), ##
                     STIGMA = c(d$STIGMA, d$STIGMA_2), ##
                     BASE_STIGMA = rep(d$STIGMA,2), ##
                     SUPPORT = c(d$SSM_TOT_PER,d$SSM_TOT_PER_2), ##
                     BASE_SUPPORT = rep(d$SSM_TOT_PER,2),
                     BISEXUAL = rep(d$BISEXUAL,2),
                     SEXORI = rep(d$SEXORI,2)

)
```

```
t = data.frame(Variables = "Missing Obs Count",
               DIS = (sum(is.na(newdata$DIS))),
                IHP = (sum(is.na(newdata$IHP))),
                PERWELLB = (sum(is.na(newdata$PERWELLB))),
                PERI_G = (sum(is.na(newdata$PERI_G))),
                SOCWELLB = (sum(is.na(newdata$SOCWELLB))),
                STIGMA = (sum(is.na(newdata$STIGMA))),
```

```
                SUPPORT = (sum(is.na(newdata$SUPPORT))))
rownames(t)= NULL

kbl(t, booktabs = T, caption = "Variables with Missing Data") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)
cc_newdata = na.omit(newdata)

model_PERWELLB <- lme(PERWELLB ~ AGE + BASE_AGE + ETHNIC + GEND + DIS +
                        BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE + SUPPORT +BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
  random =~AGE|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = cc_newdata
)

model_PERWELLB <- update(model_PERWELLB, method = 'ML' )
model_PERWELLB.reduced <- update(model_PERWELLB, fixed = PERWELLB ~ AGE + ETHNIC +
                           GEND + DIS + IHP + BISEXUAL+
                           COLSE  + SUPPORT + STIGMA,
                         method = 'ML' )
#anova(model_PERWELLB, model_PERWELLB.reduced)

t = data.frame(Model = c("Full model", "Reduced model"),
                df = c(21,15),
                AIC = c(1274.920, 1285.161),
                BIC = c(1370.732 , 1353.597 ),
                logLik = c(-616.4601,-627.5803 ),
                L.Ratio = c("-",22.24043),
                p = c("-", 0.0011))
rownames(t)= NULL

kbl(t, booktabs = T, caption = "Likelihood Ratio Test Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

model_PERWELLB <- update(model_PERWELLB, method = 'REML')
model_PERWELLB.reml.reduced <- update(model_PERWELLB, random = ~1|RID)
```

```
#1 - pmixchisq(1, 2, anova(model_PERWELLB, model_PERWELLB.reml.reduced)[2,8])
#intervals(model_PERWELLB.reml.reduced)
res = coef(summary(model_PERWELLB.reml.reduced))

t = data.frame(Effect = rep("Fixed", 16),
  Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.0591, 0.0554)",
                                      " (-0.0622, 0.0527)",
                                      " (-0.0552, 0.2683)",
                                      " (-0.1190, 0.2117)",
                                      " (-0.2178, 0.0352)",
                                      " (-0.2046, -0.0074)",
                                      " (-0.2366, 0.0510)",
                                      " (-0.3769, -0.0420)",
                                      " (-0.3073, 0.0713)",
                                      " (0.1050, 0.2505)",
                                      " (0.0570, 0.2429)",
                                      " (-0.0116, 0.0252)",
                                      " (-0.0096, 0.0413)",
                                      " (-0.0640, 0.0414)",
                                      " (-0.1307, 0.0583)",
                                      " (-0.1883, 0.0561)")),
                SE = round(as.numeric(res[2:17,2]),4),
                p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")


t1 = data.frame(Effect = c("Random", " "),
  Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.5109 (0.4609, 0.5664)",
                           "0.4105 (0.3808, 0.4427)"),
  SE = rep(" ",2),
  p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t = rbind(t,t1)

kbl(t,  format = "latex", booktabs = T, caption = "Psychological Well-Being
```

```r
    Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)
model_SOCWELLB <- lme(
  fixed = SOCWELLB ~ AGE + BASE_AGE + ETHNIC + GEND + DIS + BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE+ SUPPORT + BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
  random =~1|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = cc_newdata
)

model_SOCWELLB <- update(model_SOCWELLB, method = 'ML' )
model_SOCWELLB.reduced <- update(model_SOCWELLB, fixed = SOCWELLB ~ AGE
                                 + ETHNIC + GEND + DIS +
                           IHP + SUPPORT + BISEXUAL + STIGMA,
                         method = 'ML' )
#anova(model_SOCWELLB, model_SOCWELLB.reduced)

t = data.frame(Model = c("Full model", "Reduced model"),
               df = c(19,12),
               AIC = c(1361.462 , 1534.613 ),
               BIC = c(1448.149  , 1589.362  ),
               logLik = c(-616.4601,-755.3063 ),
               L.Ratio = c("-",187.1502),
               p = c("-", "<0.0001"))
rownames(t)= NULL

kbl(t, booktabs = T, caption = "Likelihood Ratio Test Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)
model_SOCWELLB <- update(model_SOCWELLB, method = 'REML')

#intervals(model_SOCWELLB)
res = coef(summary(model_SOCWELLB))

t = data.frame(Effect = rep("Fixed", 16),
               Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
```

```
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.1168, 0.0124)",
                                      " (-0.0067, 0.1228)",
                                      " (-0.1032, 0.2173)",
                                      " (-0.0847, 0.2428)",
                                      " (-0.3301, -0.0798)",
                                      " (-0.1790, 0.0425)",
                                      " (-0.2134, 0.0818)",
                                      " (-0.3091, 0.0669)",
                                      " (-0.2319, 0.1697)",
                                      " (0.2909, 0.4543)",
                                      " (0.03147, 0.2245)",
                                      " (-0.0148, 0.0265)",
                                      " (-0.0193, 0.0330)",
                                      " (-0.3100, 0.0352)",
                                      " (-0.1828, 0.0298)",
                                      " (-0.1374, 0.1150)")),
                SE = round(as.numeric(res[2:17,2]),4),
                p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")


t1 = data.frame(Effect = c("Random", " "),
                Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.4746 (0.4214, 0.5346)",
                             "0.4728 (0.4386, 0.5096)"),
                SE = rep(" ",2),
                p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t = rbind(t,t1)

kbl(t, booktabs = T, caption = "Social Well-Being Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

plot(model_SOCWELLB, main = "Plot of residuals vs. fitted.",col = "black")
qqnorm(model_SOCWELLB, ~ residuals(., type="pearson"),col = "black",
```

```r
      main = "QQ-Plot")
plot(model_SOCWELLB, SOCWELLB ~ fitted(.), main = "Observed vs. Fitted",
     col = "black")

model_PERI_G <- lme(
  fixed = PERI_G ~ AGE + BASE_AGE + ETHNIC + GEND + DIS + BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE + SUPPORT + BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
  random =~AGE|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = cc_newdata
)

model_PERI_G <- update(model_PERI_G, method = 'ML' )
model_PERI_G.reduced <- update(model_PERI_G, fixed = PERI_G ~ AGE + ETHNIC +
                           GEND + DIS + IHP + BISEXUAL+
                           COLSE  + SUPPORT + STIGMA,
                         method = 'ML' )
#anova(model_PERI_G, model_PERI_G.reduced)

t = data.frame(Model = c("Full model", "Reduced model"),
               df = c(21,15),
               AIC = c(1339.040 , 1344.551 ),
               BIC = c(1434.851  , 1412.988  ),
               logLik = c(-648.5200,-657.2757 ),
               L.Ratio = c("-",17.51136),
               p = c("-", 0.0076))
rownames(t)= NULL

kbl(t, booktabs = T, caption = "Likelihood Ratio Test Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

model_PERI_G <- update(model_PERI_G, method = 'REML')
model_PERI_G.reml.reduced <- update(model_PERI_G, random = ~1|RID)

#1 - pmixchisq(1, 2, anova(model_PERI_G, model_PERI_G.reml.reduced)[2,8])
#intervals(model_PERI_G.reml.reduced)
res = coef(summary(model_PERI_G.reml.reduced))

t = data.frame(Effect = rep("Fixed", 16),
```

```r
               Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.0609, 0.0707)",
                                      " (-0.0783, 0.0535)",
                                      " (-0.4037, -0.1057)",
                                      " (-0.3152, -0.0107)",
                                      " (-0.0127, 0.2198)",
                                      " (0.0076, 0.2325)",
                                      " (0.0714, 0.3540)",
                                      " (0.0953, 0.4769)",
                                      " (-0.1124, 0.2811)",
                                      " (-0.1624, 0.0034)",
                                      " (0.1101, 0.0762)",
                                      " (-0.0176, 0.0243)",
                                      " (-0.0412, 0.0090)",
                                      " (-0.2733, 0.0475)",
                                      " (-0.0377, 0.1784)",
                                      " (-0.0970, 0.1457)")),
                SE = round(as.numeric(res[2:17,2]),4),
                p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t1 = data.frame(Effect = c("Random", " "),
  Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.4115 (0.3573, 0.4740)",
                           "0.4914 (0.4557, 0.5298)"),
                  SE = rep(" ",2),
                p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t = rbind(t,t1)

kbl(t, booktabs = T, caption = "PERI Guilt Score Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

par(mfrow = c(1, 2))
```

```r
plot(model_PERI_G.reml.reduced, main = "Plot of residuals vs. fitted.",
     col = "black")
qqnorm(model_PERI_G.reml.reduced, ~ residuals(., type="pearson"),col = "black",
       main = "QQ-Plot")
plot(model_PERI_G.reml.reduced, PERI_G ~ fitted(.), main = "Observed vs. Fitted",
     col = "black")

model_PERWELLB <- lme(PERWELLB ~ AGE + BASE_AGE + ETHNIC + GEND + DIS +
                        BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE + SUPPORT +BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
  random =~1|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = newdata,
  na.action = na.omit
)
res = coef(summary(model_PERWELLB))

t = data.frame(Effect = rep("Fixed", 16),
  Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.0606, 0.0546)",
                                      " (-0.0615, 0.0541)",
                                      " (-0.0546, 0.2651)",
                                      " (-0.1139, 0.2132)",
                                      " (-0.2251, 0.0257)",
                                      " (-0.1919, 0.0045)",
                                      " (-0.2447, 0.0409)",
                                      " (-0.3910, -0.0550)",
                                      " (-0.2942, 0.0840)",
                                      " (0.0953, 0.2409)",
                                      " (0.0689, 0.2529)",
                                      " (-0.0109, 0.0262)",
                                      " (-0.0084, 0.04207)",
                                      " (-0.0732, 0.27026)",
                                      " (-0.1257, 0.0630)",
                                      " (-0.1914, 0.0521)")),
                SE = round(as.numeric(res[2:17,2]),4),
```

```
                p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")


t1 = data.frame(Effect = c("Random", " "),
  Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.5069 (0.4572, 0.5619)",
                           "0.4146 (0.3847, 0.4467)"),
  SE = rep(" ",2),
  p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t = rbind(t,t1)

kbl(t,  format = "latex", booktabs = T, caption = "Psychological Well-Being
    Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

model_SOCWELLB <- lme(
  fixed = SOCWELLB ~ AGE + BASE_AGE + ETHNIC + GEND + DIS + BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE+ SUPPORT + BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
  random =~1|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = newdata,
  na.action = na.omit
)
res = coef(summary(model_SOCWELLB))

t = data.frame(Effect = rep("Fixed", 16),
               Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.1160, 0.0122)",
                                      " (-0.0065, 0.1219)",
                                      " (-0.0978, 0.2199)",
```

```
                                       " (-0.0791, 0.2457)",
                                       " (-0.3242, -0.0763)",
                                       " (-0.1789, 0.0405)",
                                       " (-0.2143, 0.0779)",
                                       " (-0.3084, 0.0647)",
                                       " (-0.2294, 0.1694)",
                                       " (0.2907, 0.4523)",
                                       " (0.03409, 0.2244)",
                                       " (-0.0151, 0.0259)",
                                       " (-0.0188, 0.0330)",
                                       " (-0.3053, 0.0365)",
                                       " (-0.1786, 0.0309)",
                                       " (-0.1408, 0.1085)")),
                 SE = round(as.numeric(res[2:17,2]),4),
                 p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")


t1 = data.frame(Effect = c("Random", " "),
                Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.4728 (0.4200, 0.5323)",
                           "0.4706 (0.4368, 0.5070)"),
                SE = rep(" ",2),
                p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t = rbind(t,t1)

kbl(t, booktabs = T, caption = "Social Well-Being Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

plot(model_SOCWELLB, main = "Plot of residuals vs. fitted.",col = "black")
qqnorm(model_SOCWELLB, ~ residuals(., type="pearson"),col = "black",
       main = "QQ-Plot")
plot(model_SOCWELLB, SOCWELLB ~ fitted(.), main = "Observed vs. Fitted",
     col = "black")

model_PERI_G <- lme(
  fixed = PERI_G ~ AGE + BASE_AGE + ETHNIC + GEND + DIS + BASE_DIS + IHP +
    BASE_IHP + COLSE + BASE_COLSE + SUPPORT + BASE_SUPPORT + BISEXUAL + STIGMA +
    BASE_STIGMA,
```

```
  random =~1|RID,
  correlation = NULL, # Defaults to sigma^2 I
  method = 'REML',
  data = newdata,
  na.action = na.omit
)

res = coef(summary(model_PERI_G))

t = data.frame(Effect = rep("Fixed", 16),
               Variables = c("AGE", "BASE_AGE","ETHNIC: Black/African-American",
                             "ETHNIC: Latino/Hispanic","GENDER: FEMALE",
                             "DIS","BASE_DIS", "IHP","BASE_IHP","COLSE",
                             "BASE_COLSE","SUPPORT","BASE_SUPPORT",
                             "BISEXUAL","STIGMA",
                             "BASE_STIGMA"),
                Coefficient = paste(round(as.numeric(res[2:17,1]),4),
                                    c(" (-0.0613, 0.0717)",
                                      " (-0.0788, 0.0544)",
                                      " (-0.4151, -0.1201)",
                                      " (-0.3301, -0.0283)",
                                      " (-0.0238, 0.2068)",
                                      " (0.0243, 0.2488)",
                                      " (0.0762, 0.3568)",
                                      " (0.0740, 0.4565)",
                                      " (-0.1023, 0.2902)",
                                      " (-0.1585, 0.0079)",
                                      " (-0.1184, 0.0662)",
                                      " (-0.0194, 0.0229)",
                                      " (-0.0399, 0.0099)",
                                      " (-0.2942, 0.0213)",
                                      " (-0.0635, 0.1510)",
                                      " (-0.0737, 0.1668)")),
                SE = round(as.numeric(res[2:17,2]),4),
                p = round(as.numeric(res[2:17,5]),4))
colnames(t)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")

t1 = data.frame(Effect = c("Random", " "),
  Variables = c("sd(Intercept | RID)", "sd(Residual)"),
                Estimate = c("0.4058 (0.3511, 0.4690)",
                           "0.4994 (0.4635, 0.5380)"),
                  SE = rep(" ",2),
                p = rep(" ",2))
colnames(t1)= c("Effect", "Variables", "Estimate (95% CI)", "SE", "p")
```

```
t = rbind(t,t1)

kbl(t, booktabs = T, caption = "PERI Guilt Score Model Results") %>%
  kable_styling(latex_options = "HOLD_position") %>%
  column_spec(1, bold=T) %>%
  collapse_rows(columns = 1, latex_hline = "major", valign = "middle")%>%
  kable_styling(font_size = 10)

par(mfrow = c(1, 2))
plot(model_PERI_G, main = "Plot of residuals vs. fitted.",col = "black")
qqnorm(model_PERI_G, ~ residuals(., type="pearson"),col = "black",
       main = "QQ-Plot")
plot(model_PERI_G, PERI_G ~ fitted(.), main = "Observed vs. Fitted",
     col = "black")
```