

THE DIMENSIONS OF MENTAL HEALTH AND VIOLENCE AMONG
STUDENTS IN 9TH TO 12TH GRADE

A RESEARCH PAPER

SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE

MASTER OF SCIENCE

BY

MERLIN STAR

DR. HOLMES FINCH -ADVISOR

BALL STATE UNIVERSITY

MUNCIE, INDIANA

JULY 2021

Table of Contents

Acknowledgements	3
Intro.....	4
Method	6
Sampling Method	6
Procedure for Analysis	7
Results	8
Latent Class Analysis	8
Classical Test Theory Item Analysis and Item Response Theory	11
Validity	12
Reliability	13
Discussion.....	14
Discussion of Results	14
Future Studies and Limitations	15
Appendix.....	17
Tables	17
Figures	31
Bibliography	34

Acknowledgements

I give my gratitude to Dr. Holmes Finch and Dr. Jocelyn Bolin for giving me additional training in statistics. In addition, I give my thanks for both showing interest in me completing this research paper.

Intro

Mental health and violence has long been misunderstood by the populace. Numerous myths about mental health are still commonly believed despite decades of research showing otherwise. One common myth is that people with mental health problems are more likely to commit violence. This is false not only because most people with mental health issues are peaceful, but that only a specific subset of people with mental health issues are more likely to commit violence. Those that are more likely to commit violence have a history of violence and substance abuse of alcohol (Håkansson & Jesionowska, 2018). This extends to severe cases where individuals were hospitalized with those who committed violence and abused substances being the only subset within the population that were more likely to commit violence (Stone, 2018). Does this connection extend to the youth where most subsets of the population are nonviolent with a particular group being more likely to cause violence? If this does extend, late adolescence should be examined first since adolescence shares some similarities with adults, particularly for self-esteem (Masselink et al., 2017). Self-esteem is often correlated with mental health, so if a pattern was found for self-esteem, patterns for mental health should also be examined. People in high school are quite vulnerable to being shaped by both mental health and violence as for many, the teen years establish a formation of future years. Poor mental health, violence, or both are associated with adverse outcomes, including poorer academic achievement, dropping out of school, and reduced future income (Brener et al., 2013). Different types of mental conditions along with different types of violence impact the general population in different ways with different consequences. For example, studies have found that for veterans that voluntary recruitment had lower rates of PTSD compared to those forced into war (Hecker et al., 2013).

This indicates that a person's desire does factor into how violence is perceived. Additionally, the timespan of violence matters. Students who grow up with parental abuse are more likely to have depression, anxiety, and PTSD than those who do not (Peltonen et al., 2010). In addition, seeing acts of violence that occurred within the past 24 hours increased the chance of misconduct for the next 24 hours. Lastly, adolescents who showed greater increases in conduct problem symptoms and health-risk behavior on the days that they were exposed to violence days were more likely to use substances (Odgers & Russell, 2017). Clearly, mental health and violence have a relationship on each other and both can negatively impact high school students. To fully understand the problem though, one must look more in depth at what past researchers have done for the adolescent and young adult population.

Past research with adolescence has shown that many effects from adolescence carry over into adulthood. For example, being directly exposed to a single incident traumatic event such as 9/11 has detrimental effects of increased PTSD, depression, problematic behavior, and having 2 or more mental health diagnoses (Gargano et al., 2018). In addition, problematic behavior tends to be correlated, as Wartberg & Kammerl in 2020 shows. Their study looked at adolescents who had problematic use of alcohol, internet, video games, and social media and found that all 4 problematic behaviors were correlated with one another. It is likely that problematic behavior clusters as a means to distress using maladaptive coping. There are several ways to make a study to examine problematic behavior in adolescence for trajectory purposes in the population and once such study is called the Youth Risk Behavior Surveillance System.

The Youth Risk Behavior Surveillance System (YRBS) is a questionnaire that asks questions about numerous things, but the questions relevant to this paper are numbered 12-29 violence

directed at others, violence directed at them, rape, sexual assault, dating violence, bullying, and suicide. For violence, sexual assault, and rape specifically, a study was done in 2008 by Hanson and others and found that girls had higher rates of sexual abuse and assault than boys, but both genders had equal rate of physical violence. For bullying, those that were victims of bullying, bullied others, or did both had higher rates of depression, lower amounts of sleep compared, and lower GPA to those not bullied. Additionally, bullies and bully victims (those that both bullied and were bullied) had higher levels of conduct problems, though this does not extend to victims (Hysing et al., 2019). Lastly, self-harm is also associated with bullying for victims (Fisher et al., 2012). As for suicide, there is a well-known link between depression, conduct problems, and substance abuse that all increase the chance of attempted and completed suicide (Vander et al., 2011). Clearly a link between mental health, violence, and bullying exists. This paper seeks to establish the subpopulations within the high school population to determine what groups are more at risk of detrimental effect than others and how each subgroup differs.

Method

Sampling Method

The sample of students in grades 9 to 12 in America ($N=13,677$, $N_{\text{complete cases}}=6,788$) included in this database was identified through ICF Macro, an international company, with Center of Disease Control and Prevention oversight. Together they identify appropriate schools, gain clearance to survey the schools, obtain parental permission, and other requirements for the survey. YRBS was the dataset chosen for this problem because it is designed to be used to describe the prevalence of health-risk behaviors among youths along with health-risk trends.

YRBS focuses almost exclusively on health-risk behaviors rather than what determines the behaviors because of a more direct link on the outcomes than between determinants of behaviors and health outcomes (Centers for Disease Control and Prevention, 2019). Additionally, YRBS is available to the public, allowing others to freely access the data. However this dataset has the limitation of 4 states not using it (Minnesota, Oregon, Washington, and Wyoming do not participate in this survey) and missing data. The most recent survey as of June 2021 is dated 2019, so this sample was used. After this sample was collected, further data reduction was done for the data analysis.

Procedure for Analysis

For this data analysis, latent class analysis, classical test theory item analysis, and item response theory will be used. Each of these are specialty analysis designed to look at underlying classes for tests. Two to four classes will be tested as appropriate. To ensure each analysis is appropriate, all assumptions for each model must be examined. For latent class analysis, the assumption is conditional independence, which assumes that for 2 independent categories that the probability of being in a subset is $S_a * S_b = S_{ab}$ with a being a subset of 1 category and b being a subset of a 2nd category. This is a reasonable assumption for this dataset considering each category. For item response theory, in addition to conditional independence, 2 more assumptions are made. One is that there is a unidimensional trait and the other is that the response of a person to an item can be modeled by a mathematical item response function. As long as the questions are broken into each dimension by the corresponding section, both assumptions are held. Lastly, for classical test theory item analysis, there are 4 main assumptions. These are that the expected value of

measurement error within a person is zero, the expected value of measurement error across persons in the population is zero, true score is uncorrelated with measurement error in the population of persons, the variance of observed scores across persons is equal to the sum of the variances of true score and measurement error, and measurement errors of different tests are not correlated. Each of these assumptions are unlikely to be true as measurement error is likely to be positive and correlated with the true score due to sensitive questions being answered and the data are not missing at random.

Results

Latent Class Analysis

The latent class analysis used the entire dataset. From the results, 3 classes would be ideal.

Above 3 classes, one of the group sizes becomes much smaller than the others, making it difficult to assess whether it is random noise or a true subset of the population. All numbers will be rounded to the nearest whole or nearest tenth. 3 classes will be discussed fairly in depth. To see the statistics in the remaining classes, see the R code attachment named “Capstone.pdf”.

First, there will be an analysis of the entire question set, then a subset of question 12-22 and 23-29.

This part is for all the included questions. For question 12-18 and 20, all 3 classes has over a 50% conditional probability of answering A to question 12. However, Class 3 has an increased probability of answering B to H compared to classes 1 and 2. In addition, classes 1 and 2

consistently answered A at least 10% of the time more than class 3. For full details of the latent class analysis for 3 classes, see Table 1. For question 19, classes 1 and 2 had over a 95% conditional probability of answering B, while class 3 only had a 69% chance of answering B. Questions 21 and 22 diverged significantly from the other questions. Class 1, 2 and 3 were quite distinct with their answer choices. No one in class 1 answered A. Over 96% answered B with the rest answering C to F. For class 2, all answered A only. For class 3, around 20% answered A, 56% answered B, 9% answered C, and the rest chose D to F. Questions 23-27 had classes 1 and 2 answer B at least 70% of the time. However, class 3 consistently answered B far less than class 1 or 2, sometimes even having as low as 15.3% of answering B compared to 73% and 75% for question 27 as an example. Question 28 had classes 1 and 2 answer A 99% of the time and answer B the remaining 1%. For class 3, they answered A 48% of the time, B 27% of the time, C 17% of the time, D 3% of the time and E 4% of the time. Lastly, question 29 had class 1 always answer A, class 2 had 99.9% answer A with .1 answering C, and class 3 answered A 47% of the time, B 15% of the time, and C 38% of the time. The 3 groups had an estimate class population share of 50.6% in group 1, 30.5% in group 2, and 18.9% in group 3. The maximum log-likelihood was -91,052, the residual degrees of freedom were 13,486, the AIC was 182,485, the BIC was 183,922, the likelihood ratio/deviance statistic was 26,432 and χ^2 was $1.7 * 10^{15}$.

For the subset questions 12-22, 1-4 classes were tested. 2 classes best describe the subset, so 2 classes will be discussed fairly in depth. To see the other classes in detail, see the R code attachment named “Capstone.pdf”. For question 12-20, the 2 classes answered similarly to the questions. For the full details of the 2 class model, see Table 2. However, questions 21 and 22, the 2 classes diverged. For questions 21 and 22, class 2 always answered A, while class 1 never

answered A. In addition, class 1 answered B over 90% of the time, and answered C-F the remaining 10% of the time. For a visualization of this, see Figure 1.

For the subset questions 23-29, 1-3 classes were tested. 2 classes best describe the subset, so 2 classes will be discussed fairly in depth while 1 and 3 classes will be briefly discussed. Overall, the 2 classes were quite different. For the full details of the 2 class model, see Table 3. For a visualization of this, see Figure 2. Questions 23 and 24 had class 1 answer A and B rather evenly, while class 2 had 85% or more answer B with the remaining answering A. For question 25, class 1 answered A 88% of the time and B 12% of the time, while class 2 answered A 25% of the time and B 75% of the time. For questions 26 and 27, class 1 answered A over 70% of the time with remaining responses in B while class 2 answered B over 95% of the time. Questions 28 and 29 had class 2 answer all A, while class 1 answered A 50% of the time, and answered other answer options the other 50%. In total, the estimated class population share is 19% in class 1 and 81% in class 2, the maximum log-likelihood was -34,367, the residual degrees of freedom were 456, the AIC was 68,781 the BIC was 68,954, the likelihood ratio/deviance statistic was 4651 and χ^2 was 6388.

1 class is the loglinear independence model, so this can be estimated in a number of different ways, though this will be estimated in a similar way to more than 1 class. For this, the residual degrees of freedom were 468, the maximum log-likelihood was -41,773, the AIC was 83,569, the BIC 83,651, the likelihood ratio/deviance statistic was 16114, and χ^2 was 1,696,832. The latent class analysis for 3 groups had an estimate class population share of 9.4% in group 1, 67.6% in group 2 and 23% in group 3. The maximum log-likelihood was -32810, the residual degrees of

freedom were 444, the AIC was 65,689, the BIC was 65,953, the likelihood ratio/deviance statistic was 1,875 and χ^2 was 2,769.

Classical Test Theory Item Analysis and Item Response Theory

For this section, assume only complete cases are used until otherwise. For classical test theory, questions 21 and 22 had A and B combined since both were desirable answers. The results showed an extremely low validity for all questions. For more detail, see Table 4. For the item analysis, it is divided into questions 12-22 and 23-29 with the unaltered questions 21 and 22. An r correlation was ran and everything came up significant, however the Type 1 error is likely extremely inflated, so caution is advised when interpreting this. To see all the r correlations, look at Table 5. The Graded Response Model was used because it can handle multiple responses. For all the graded response models (GRM), R gave an error of producing NAs but gave no explanation as to why this happened. For more details, see the R code attached named “Capstone.pdf”. The summary of the GRM without constraint can be found in Table 6. The general pattern is that the first 2 questions have the biggest increases in extremity parameters followed by a slow increase for the remaining questions. A similar pattern can be found for the summary of the GRM with constraint in Table 7. Both GRMs had poor fits as can be seen in Tables 8 and 9. For the GRMs without constraint for questions 23-29, the extremity values were all negative. In addition, the extremity values became much more negative with higher values. For the GRMs with constraint for questions 23-29, only questions 28 and 29 had positive extremity value. Without constraint, only question 24 with question 27 had no lack of fit issue.

With constraint, all had a lack of fit issue. For details on the GRMs without and with constraint, see Tables 10 and 11.

Validity

To check validity, factor analysis and principal component analysis was used. The entire dataset was used for this section. The 3 rotations that seemed suitable were: 3 factors without rotation in factor analysis, 4 factors without rotation in factor analysis, and 3 factor principal axis with promax rotation. For 3 factors without rotation on factor analysis, factor 1 loaded strongly to questions 26-29 and somewhat strongly on to 25, factor 2 loaded strongly to questions 20-22, and factor 3 loaded strongly on to 12, 14, 16-18 and somewhat strongly to question 13. The sum of squared loading (SS loadings) was 2.756 for factor 1, 2.359 for factor 2, and 1.662 for factor 3. The proportion variation was 15.3% for factor 1, 13.1% for factor 2, and 9.2% for factor 3 for a total of 37.7% variation. For the summary, see Table 12.

For 4 factors without rotation on factor analysis, factor 1 loaded strongly to questions 20-22, 26-29 and somewhat strongly on to 19. Factor 2 loaded strongly to questions 17, 18, 26 and 27, and loaded somewhat strongly on to 16, 23, 25. Factor 3 loaded strongly on to 21, 28, and 29. Lastly, factor 4 loaded strongly on 17, 18, 25, and 26 with a somewhat strong loading on 14 and 25. The sum of squared loading was 3.317 for factor 1, 1.565 for factor 2, 1.465 for factor 3, and 1.399 for factor 4. The proportion variation was 18.4% for factor 1, 8.7% for factor 2, and 8.1% for factor 3, and 7.8% for factor 4 for a total of 43% variation. For the summary, see Table 13.

For the 3 factor principal axis with promax rotation, the SS loadings were 2.94, 2.29, and 2.02 for the 3 factors. The proportion of variance explained by each is 16%, 13%, and 11% to make a total of 40%. The factor correlation were -.36 for factor 2 with factor 1, -.54 for factor 3 with factor 1, and .49 for factor 2 with factor 3. The mean item complexity is 1.1. χ^2 is 88012, degrees of freedom for the null model is 153, objective function of null model is 6.44, degrees of freedom for the model is 102, objective function of model is 1.44, root mean square of the residuals (RMSR) is 0.06, the degrees of freedom corrected root mean square of the residuals is 0.07, the Tucker Lewis Index of factoring reliability is 0.665, the RMSEA index is 0.119 (90% CI .12, .117), the BIC is 18,765, and the fit based upon off diagonal values is 0.95.

Principal component analysis was then used. The full display results are in Table 15. The results showed that most questions did not load on to many components and that the majority of components that they did load on was weak.

Reliability

For this section, assume the full dataset is used unless otherwise indicated. The reliability for this specific population with questions 12-29 was Cronbach's alpha (α) of .65 (95% CI .65, .66) without score reversal and $\alpha = .8$ (95% CI .8, .81) with score reversal. Score reversal was justified in this case because some questions were encoded reversed compared to other questions.

Questions 19, 23-27 were reversed for the full dataset. However, these questions are known to not be measuring just 1 dimension, so questions 12-22 and questions 23-29 will be examined

separately. For questions 12-22 with score reversal, $\alpha = .74$ (95% CI .74, .75). For question 23-29 with score reversal, $\alpha = .74$ (95% CI .74, .75). The split halves reliability estimate is .775. The Guttman reliability estimates were maximum split half reliability of 0.91, average split half reliability of 0.82, a minimum split half reliability of 0.59, and an average interitem r of 0.21 with median of 0.18. For the greatest lower bound, an estimate of the communalities factor model where the number of factors is the number with positive eigen values was used. Questions 15 and 19 were below .3, questions 13, 14, and 25 were below .4, questions 16, 18, 23, 24, 25, 27 were below .6, and the others were above .6. For McDonald's Omega, it was .544 for 1 factor, .594 for 2 factors, and .645 for 3 factors. For the confidence intervals for the full data set, the 95% CI is .69 to .71 for Bonett, Feldt, Fisher, and Hakstain. With only using complete cases for percentile bootstrap confidence interval, bias-corrected and accelerated bootstrap confidence interval, and asymptotic distribution-free method, the 95% CI was .54 to .64, which indicates that noncomplete cases do affect alpha.

Discussion

Discussion of Results

The results clearly showed that classical test theory and item response theory were not well suited for this dataset. This is likely due to the large amount of missing data and that measurement error is likely to be above zero and correlated with scores. For validity, multiple factor analysis showed that there were likely 3 or 4 underlying variables, which confirms that the

subset of questions YRBS was asking really were distinct and fell into 3 or 4 areas. The reliability for this specific population for complete cases for this particular test was .8, which is good and backed up by previous studies that alpha is relatively stable and stays around the .7 to .8 range for the national high school students survey (Centers for Disease Control and Prevention, 2019). Unfortunately without complete cases, this survey seems to be no longer reliable for this specific population. As for the latent class analysis, it appears this dataset has 3 specific subpopulations. The 1st subpopulation were people that did date and generally reported mental health issues and violence in low numbers. The 2nd subpopulation were people that did not date and generally reported mental health issues and violence in low numbers. The 3rd subpopulation was the most interesting of all since their scores were consistently quite elevated for mental health issues. That last group is estimated to make up around 19% of the sampled population and has some worrying statistics. 76% of the 3rd group seriously considered attempting suicide in the past year, 51% were bullied on school property, 45% were electronically bullied, over 50% attempted suicide once or more in the past year, and 30% of them were raped. They also had elevated rates of violence, though not nearly as high as the elevation of mental conditions. Clearly the 3rd subpopulation is at a much higher risk of poorer quality of life compared to the other 2 groups. Future studies should target this specific subpopulation for further divisions within this group, interventions, and longitudinal studies.

Future Studies and Limitations

One major clue of where future studies could lead is a 2019 study where they looked into cyberbullying, mental health, and violence in adolescents and associations with sex and race. This study found that those cyberbullied had elevated depression, suicidal thoughts and attempts, were more likely to carry weapons. In addition, the most likely victims were white non-Hispanic

females (Alhajji et al., 2019). Future studies could look more specifically into cyberbullying and how the patterns may differ from in person bullying. In addition, future studies can also look into how substance abuse factors into all of this. In person bullying in adolescence is already known to increase rates of depression, but does cyberbullying affect this differently (Winding et al., 2020)? Would cyberbullying have different patterns of depressive symptoms compared to bullying? Only future studies can determine that. Another future study can also look into how school specific stress factors into this as school stress is the most common stressor among adolescence (Anniko et al., 2019). How does school stress differ from stress at home or possibly stress from other factors, such as war or food instability? Stress from family violence is unfortunately common, yet this is routinely overlooked when diagnosing adolescents with mental health disorders, which can lead to inappropriate treatments, prolonged exposure to abusive environments, and expose adolescents to further risks (Bunston et al., 2017). Lastly, community violence should be examined more carefully. Community violence also impacts adolescents' mental health and safety and it is associated with increased rates of depression (Copeland-Linder et al., 2010).

There are limitations of this study. First, race, sex, individual age and ethnicity were not examined individually. Second, drugs were not examined despite there being evidence that they also impact mental health and violence. Third, the YRBS does not have information on 4 states, so researchers that want to specifically study those states should not assume that YRBS will automatically apply to them. Lastly, YRBS has a lot of missing data, which makes drawing any firm conclusions difficult, especially since the data are not missing at random.

Appendix

Tables

Table 1

Code display of the 3 class polytomous latent class analysis for all relevant questions

```
> lca.polca3 =  
poLCA(cbind(q12,q13,q14,q15,q16,q17,q18,q19,q20,q21,q22,q23,q24,q25,q26,q27,q  
28,q29)~1,nclass=3,data=reduceddata,nrep=3,na.rm=F,graphs=T,maxiter = 50000)
```

Model 1: llik = -91051.65 ... best llik = -91051.65

Model 2: llik = -94597.68 ... best llik = -91051.65

Model 3: llik = -91051.59 ... best llik = -91051.59

Conditional item response (column) probabilities,
by outcome variable, for each class (row)

\$q12

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.8843	0.0257	0.0265	0.0120	0.0515
class 2:	0.9226	0.0192	0.0273	0.0064	0.0246
class 3:	0.7238	0.0571	0.0657	0.0327	0.1207

\$q13

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9846	0.0046	0.0012	0.0013	0.0083
class 2:	0.9911	0.0038	0.0020	0.0000	0.0032
class 3:	0.8927	0.0339	0.0221	0.0114	0.0399

\$q14

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9619	0.0087	0.0106	0.0046	0.0142
class 2:	0.9871	0.0048	0.0034	0.0021	0.0027
class 3:	0.8758	0.0304	0.0292	0.0160	0.0485

\$q15

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9417	0.0362	0.0162	0.0027	0.0031
class 2:	0.9563	0.0260	0.0127	0.0027	0.0024
class 3:	0.7309	0.1007	0.0931	0.0282	0.0471

\$q16

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.9549	0.0276	0.0124	0.0022	0.0004	0.0006	0.0002	0.0018
class 2:	0.9755	0.0162	0.0051	0.0014	0.0008	0.0000	0.0000	0.0010
class 3:	0.7408	0.0919	0.0722	0.0320	0.0184	0.0089	0.0066	0.0291

\$q17

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.7891	0.1036	0.0709	0.0195	0.0063	0.0014	0.0014	0.0077
class 2:	0.8861	0.0603	0.0329	0.0077	0.0042	0.0016	0.0000	0.0073
class 3:	0.5684	0.1595	0.1415	0.0482	0.0198	0.0125	0.0062	0.0440

\$q18

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.9254	0.0530	0.0166	0.0026	0.0011	0.0003	0.0005	0.0005
class 2:	0.9674	0.0197	0.0102	0.0013	0.0009	0.0000	0.0000	0.0005
class 3:	0.7788	0.1060	0.0604	0.0132	0.0100	0.0059	0.0019	0.0239

\$q19

	Pr(1)	Pr(2)
class 1:	0.0321	0.9679
class 2:	0.0211	0.9789
class 3:	0.3075	0.6925

\$q20

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9426	0.0362	0.0157	0.0024	0.0029
class 2:	0.9722	0.0188	0.0068	0.0013	0.0009
class 3:	0.5713	0.1316	0.1622	0.0525	0.0824

\$q21

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)
class 1:	0.0000	0.9782	0.0137	0.0056	0.0015	0.001
class 2:	1.0000	0.0000	0.0000	0.0000	0.0000	0.000
class 3:	0.1882	0.5616	0.0892	0.0948	0.0181	0.048

\$q22

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)
class 1:	0.0000	0.9650	0.0203	0.0094	0.0013	0.0041
class 2:	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
class 3:	0.1991	0.5692	0.0894	0.0621	0.0219	0.0582

\$q23

	Pr(1)	Pr(2)
class 1:	0.1320	0.8680
class 2:	0.1267	0.8733
class 3:	0.5199	0.4801

\$q24

	Pr(1)	Pr(2)
class 1:	0.1049	0.8951
class 2:	0.0728	0.9272
class 3:	0.4521	0.5479

\$q25

	Pr(1)	Pr(2)
class 1:	0.2696	0.7304
class 2:	0.2442	0.7558
class 3:	0.8471	0.1529

\$q26

	Pr(1)	Pr(2)
class 1:	0.0618	0.9382
class 2:	0.0821	0.9179

class 3: 0.7614 0.2386

\$q27

	Pr(1)	Pr(2)
class 1:	0.0400	0.9600
class 2:	0.0681	0.9319
class 3:	0.6533	0.3467

\$q28

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9892	0.0108	0.0000	0.0000	0.0000
class 2:	0.9919	0.0080	0.0001	0.0000	0.0000
class 3:	0.4844	0.2729	0.1671	0.0351	0.0404

\$q29

	Pr(1)	Pr(2)	Pr(3)
class 1:	1.0000	0.0000	0.0000
class 2:	0.9990	0.0000	0.0010
class 3:	0.4673	0.1481	0.3846

Estimated class population shares

0.5058 0.3052 0.189

Predicted class memberships (by modal posterior prob.)

0.5164 0.3011 0.1825

=====
Fit for 3 latent classes:

=====
number of observations: 13677
number of fully observed cases: 6788
number of estimated parameters: 191
residual degrees of freedom: 13486
maximum log-likelihood: -91051.59

```

AIC(3): 182485.2
BIC(3): 183922.2
G^2(3): 26432.61 (Likelihood ratio/deviance statistic)
X^2(3): 1.666077e+15 (Chi-square goodness of fit)

```

Table 2

Code display of the 2 class polytomous latent class analysis for questions 12-22

```

> subset1.lca =
poLCA(cbind(q12,q13,q14,q15,q16,q17,q18,q19,q20,q21,q22)~1,nclass=2,data=redu
ceddata,nrep=3,na.rm=F,graphs=T,maxiter = 50000) #2 classes

```

```
Model 1: llik = -60939.08 ... best llik = -60939.08
```

```
Model 2: llik = -60939.08 ... best llik = -60939.08
```

```
Model 3: llik = -58460.34 ... best llik = -58460.34
```

```
Conditional item response (column) probabilities,
by outcome variable, for each class (row)

```

\$q12

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9059	0.0215	0.0309	0.0101	0.0315
class 2:	0.8477	0.0333	0.0352	0.0160	0.0679

\$q13

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9831	0.0061	0.0037	0.0002	0.0069
class 2:	0.9626	0.0117	0.0061	0.0041	0.0155

\$q14

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9765	0.0068	0.0068	0.0033	0.0066
class 2:	0.9420	0.0140	0.0144	0.0072	0.0224

\$q15

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9345	0.0342	0.0186	0.0053	0.0075
class 2:	0.8921	0.0509	0.0353	0.0087	0.0130

\$q16

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.9541	0.0235	0.0106	0.0038	0.0025	0.0011	0.0004	0.0039
class 2:	0.9036	0.0429	0.0270	0.0094	0.0047	0.0025	0.0018	0.0082

\$q17

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.8621	0.0666	0.0398	0.0122	0.0056	0.0020	0.0006	0.0111
class 2:	0.7372	0.1176	0.0882	0.0255	0.0093	0.0041	0.0025	0.0156

\$q18

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)	Pr(7)	Pr(8)
class 1:	0.9518	0.0268	0.0133	0.0031	0.0016	0.0009	2e-04	0.0022
class 2:	0.8900	0.0661	0.0276	0.0048	0.0032	0.0014	8e-04	0.0061

\$q19

	Pr(1)	Pr(2)
class 1:	0.0384	0.9616
class 2:	0.0969	0.9031

\$q20

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.9507	0.0287	0.0124	0.0026	0.0056
class 2:	0.8538	0.0573	0.0521	0.0151	0.0217

\$q21

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)
class 1:	1	0.0000	0.0000	0.0000	0.0000	0.0000
class 2:	0	0.9185	0.0337	0.0288	0.0058	0.0131

\$q22

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)	Pr(6)
class 1:	1	0.0000	0.0000	0.0000	0.0000	0.0000
class 2:	0	0.9082	0.0407	0.0246	0.0071	0.0194

Estimated class population shares

0.3424 0.6576

Predicted class memberships (by modal posterior prob.)

0.3345 0.6655

```
=====
Fit for 2 latent classes:
=====
```

number of observations: 13677

number of fully observed cases: 7744

number of estimated parameters: 105

residual degrees of freedom: 13572

maximum log-likelihood: -58460.34

AIC(2): 117130.7

BIC(2): 117920.7

G²(2): 16327.11 (Likelihood ratio/deviance statistic)

X²(2): 5.661766e+16 (Chi-square goodness of fit)

Table 3

Code display of the 2 class polytomous latent classes for questions 23-29

```
> subset6.lca = polCA(cbind(q23,q24,q25,q26,q27,q28,q29)~1,
nclass=2,data=reduceddata,nrep=3,na.rm=F,graphs=T,maxiter = 50000)
```

Model 1: llik = -34367.64 ... best llik = -34367.64

Model 2: llik = -34367.64 ... best llik = -34367.64

Model 3: llik = -34367.64 ... best llik = -34367.64

Conditional item response (column) probabilities,
by outcome variable, for each class (row)

\$q23

	Pr(1)	Pr(2)
class 1:	0.4733	0.5267
class 2:	0.1370	0.8630

\$q24

	Pr(1)	Pr(2)
class 1:	0.3999	0.6001
class 2:	0.1015	0.8985

\$q25

	Pr(1)	Pr(2)
class 1:	0.8811	0.1189
class 2:	0.2464	0.7536

\$q26

	Pr(1)	Pr(2)
class 1:	0.869	0.131
class 2:	0.037	0.963

\$q27

	Pr(1)	Pr(2)
class 1:	0.7219	0.2781
class 2:	0.0284	0.9716

\$q28

	Pr(1)	Pr(2)	Pr(3)	Pr(4)	Pr(5)
class 1:	0.5207	0.2533	0.1557	0.0327	0.0376
class 2:	0.9900	0.0100	0.0000	0.0000	0.0000

\$q29

	Pr(1)	Pr(2)	Pr(3)
class 1:	0.5145	0.1345	0.351
class 2:	1.0000	0.0000	0.000

Estimated class population shares

0.1944 0.8056

Predicted class memberships (by modal posterior prob.)

0.1862 0.8138

=====
Fit for 2 latent classes:
=====

number of observations: 13677
number of fully observed cases: 8597
number of estimated parameters: 23
residual degrees of freedom: 456
maximum log-likelihood: -34367.64

AIC(2): 68781.27

BIC(2): 68954.31

G²(2): 4650.796 (Likelihood ratio/deviance statistic)

X²(2): 6387.731 (Chi-square goodness of fit)

Table 4

Classical Test Theory Item Analysis Results

	Sample.SD <dbl>	Item.total <dbl>	Item.Tot.woi <dbl>	Difficulty <dbl>	Discrimination <dbl>	Item.Criterion <dbl>	Item.Reliab <dbl>	Item.Rel.woi <dbl>	Item.Validity <dbl>
q12	1.0131470	0.587030882	0.3542018	1.350177	0.98496905	-0.3198241	0.594704737	0.35883204	-0.3240049
q13	0.4383763	0.450858742	0.3463355	1.055245	0.16445623	-0.2329624	0.197631216	0.15181409	-0.1021177
q14	0.5335124	0.512002955	0.3904850	1.091780	0.27320955	-0.2376942	0.273139825	0.20831324	-0.1268035
q15	0.5011944	0.327632825	0.1960754	1.119623	0.24491600	-0.3625368	0.164195649	0.09826467	-0.1816880
q16	0.6724832	0.526783410	0.3720161	1.137154	0.32891247	-0.3810375	0.354226898	0.25015613	-0.2562224
q17	1.0751209	0.663151605	0.4388911	1.421332	1.07427056	-0.4233798	0.712915632	0.47182621	-0.4551510
q18	0.5470344	0.619370054	0.5120086	1.115793	0.31874447	-0.3563193	0.338791778	0.28006569	-0.1949046
q19	0.2495816	-0.194620608	-0.2596183	1.933265	-0.04774536	0.4756738	-0.048570145	-0.06479118	0.1187107
q20	0.6690266	0.451871528	0.2864453	1.196523	0.43633952	-0.5265961	0.302291797	0.19162541	-0.3522808
ReducedFactorQ21	0.4848974	0.449408828	0.3327404	1.096494	0.26259947	-0.4312273	0.217901111	0.16133306	-0.2090856
ReducedFactorQ22	0.4914301	0.450030640	0.3317296	1.092369	0.24491600	-0.3884018	0.221142322	0.16300991	-0.1908583
q23	0.3960415	-0.015979532	-0.1246264	1.805245	0.10123784	0.5191187	-0.006328092	-0.04935358	0.2055774
q24	0.3579333	-0.009631632	-0.1080632	1.849146	0.09018568	0.5051677	-0.003447228	-0.03867657	0.1808030
q25	0.4858759	0.044552963	-0.0896470	1.618150	0.23297966	0.5886242	0.021645619	-0.04355411	0.2859773
q26	0.3972854	-0.044891754	-0.1531732	1.803624	0.03404067	0.6705163	-0.017833525	-0.06084900	0.2663667
q27	0.3679831	-0.070336533	-0.1700933	1.838539	0.00928382	0.6469740	-0.025880749	-0.06258684	0.2380580
q28	0.5012252	0.380861449	0.2533347	1.133471	0.27409372	-0.6182039	0.190883283	0.12696838	-0.3098365
q29	0.4982328	0.251928292	0.1170264	1.145256	0.26259947	-0.6128084	0.125509694	0.05830209	-0.3052987

Table 5

R correlations of Item Response Theory

	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26	Q27	Q28	Q29
q12	*****	0.428	0.369	0.065	0.191	0.306	0.213	-0.061	0.092	0.104	0.146	-0.073	-0.041	-0.042	0.069	-0.085	0.11	0.069
q13	<0.001	*****	0.149	0.099	0.201	0.175	0.255	-0.092	0.123	0.097	0.105	-0.059	-0.041	-0.023	0.07	-0.084	0.125	0.066
q14	<0.001	<0.001	*****	0.088	0.238	0.308	0.268	-0.081	0.114	0.112	0.136	-0.026	-0.013	-0.025	-0.023	-0.039	0.113	0.034
q15	<0.001	<0.001	<0.001	*****	0.249	0.15	0.174	-0.188	0.212	0.152	0.13	-0.181	-0.174	-0.151	0.165	-0.147	0.184	0.133
q16	<0.001	<0.001	<0.001	<0.001	*****	0.282	0.331	-0.133	0.209	0.174	0.214	-0.194	-0.182	-0.094	-0.136	-0.142	0.225	0.116
q17	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.605	-0.122	0.167	0.151	0.201	-0.112	-0.1	-0.092	-0.115	-0.115	0.178	0.114
q18	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	-0.125	0.189	0.153	0.19	-0.116	-0.096	-0.052	0.081	-0.084	0.197	0.096
q19	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	-0.456	-0.317	-0.226	0.176	0.194	0.202	0.242	0.244	-0.268	-0.236
q20	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.591	0.313	-0.203	-0.223	-0.216	0.228	-0.234	0.277	0.233
q21	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.731	-0.131	-0.18	-0.159	-0.153	-0.151	0.221	0.179
q22	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	-0.12	-0.157	-0.144	-0.149	-0.153	0.229	0.169
q23	<0.001	<0.001	0.035	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.493	0.254	0.251	0.227	-0.197	-0.195
q24	0.001	0.001	0.279	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.252	0.243	0.211	-0.198	-0.193
q25	<0.001	0.054	0.044	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.485	0.43	-0.289	-0.316
q26	<0.001	<0.001	0.061	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.672	-0.503	-0.55
q27	<0.001	<0.001	0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	-0.505	-0.527
q28	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****	0.842
q29	<0.001	<0.001	0.005	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	*****

upper diagonal part contains correlation coefficient estimates

lower diagonal part contains corresponding p-values

Table 6

Summary of Item Response Theory on questions 12-22 without constraint

Questio n 12	Questio n 13	Questio n 14	Questio n 15	Questio n 16	Questio n 17	Questio n 18	Questio n 19	Questio n 20	Questio n 21	Questio n 22
Extrmt1 1.828	Extrmt1 3.459	Extrmt1 3.136	Extrmt1 3.188	Extrmt1 2.086	Extrmt1 1.311	Extrmt1 1.771	Extrmt1 2.248	Extrmt1 2.466	Extrmt1 0.385	Extrmt1 0.526
Extrmt2 2.544	Extrmt2 3.602	Extrmt2 3.371	Extrmt2 4.266	Extrmt2 2.578	Extrmt2 1.938	Extrmt2 2.128	Dscrmn -1.682	Extrmt2 3.400	Extrmt2 1.738	Extrmt2 2.332
Extrmt3 3.376	Extrmt3 3.757	Extrmt3 3.697	Extrmt3 5.539	Extrmt3 3.144	Extrmt3 2.469	Extrmt3 2.960		Extrmt3 4.441	Extrmt3 2.266	Extrmt3 3.117
Extrmt4 3.698	Extrmt4 3.895	Extrmt4 3.909	Extrmt4 6.101	Extrmt4 3.380	Extrmt4 2.873	Extrmt4 3.109		Extrmt4 5.022	Extrmt4 3.230	Extrmt4 4.129
Dscrmn 0.967	Dscrmn 1.541	Dscrmn 1.418	Dscrmn 0.928	Extrmt5 3.584	Extrmt5 3.038	Extrmt5 3.255		Dscrmn 0.971	Extrmt5 3.622	Extrmt5 4.474
				Extrmt6 3.772	Extrmt6 3.139	Extrmt6 3.385			Dscrmn 1.416	Dscrmn 0.942

				Extrmt7 3.986	Extrmt7 3.236	Extrmt7 3.544				
				Dscrmn 1.890	Dscrmn 2.393	Dscrmn 3.167				

Integration:

method: Gauss-Hermite

quadrature points: 21

Optimization:

Convergence: 0

max(|grad|): 2393

quasi-Newton: BFGS

Table 7

Summary of Item Response Theory on questions 12-22 with constraint

Questio n 12	Questio n 13	Questio n 14	Questio n 15	Questio n 16	Questio n 17	Questio n 18	Questio n 19	Questio n 20	Questio n 21	Questio n 22
Extrmt1 1.802	Extrmt1 3.504	Extrmt1 2.968	Extrmt1 2.374	Extrmt1 2.420	Extrmt1 1.277	Extrmt1 2.354	Extrmt1 -2.426	Extrmt1 2.013	Extrmt1 -0.564	Extrmt1 -0.562
Extrmt2 2.036	Extrmt2 3.671	Extrmt2 3.193	Extrmt2 2.975	Extrmt2 3.011	Extrmt2 1.946	Extrmt2 3.229	Dscrmn 1.395	Extrmt2 2.521	Extrmt2 2.693	Extrmt2 2.763
Extrmt3 2.402	Extrmt3 3.841	Extrmt3 3.538	Extrmt3 3.887	Extrmt3 3.709	Extrmt3 2.808	Extrmt3 4.301		Extrmt3 3.309	Extrmt3 3.151	Extrmt3 3.243
Extrmt4 2.579	Extrmt4 3.947	Extrmt4 3.767	Extrmt4 4.301	Extrmt4 4.034	Extrmt4 3.373	Extrmt4 4.580		Extrmt4 3.711	Extrmt4 3.881	Extrmt4 3.826
Dscrmn 1.395	Dscrmn 1.395	Dscrmn 1.395	Dscrmn 1.395	Extrmt5 4.293	Extrmt5 3.637	Extrmt5 4.823		Dscrmn 1.395	Extrmt5 4.221	Extrmt5 4.034
				Extrmt6 4.473	Extrmt6 3.772	Extrmt6 4.898			Dscrmn 1.395	Dscrmn 1.395
				Extrmt7 4.621	Extrmt7 3.869	Extrmt7 4.939				
				Dscrmn 1.395	Dscrmn 1.395	Dscrmn 1.395				

Integration:

method: Gauss-Hermite

quadrature points: 21

Optimization:

Convergence: 0

max(|grad|): 0.079

quasi-Newton: BFGS

Table 8

Fit of the Item Response Theory on Questions 12-22 without constraint

Fit on the Two-Way Margins

	q12	q13	q14	q15	q16	q17	q18	q19	q20	q21	q22
q12	-	1114.75	755.91	380.78	384.61	824.56	493.54	359.93	396.44	4383.06	4477.56
q13	***	-	64.67	83.85	80.22	401.87	177.61	16.71	81.25	3719.85	3806.61
q14	***		-	89.42	92.63	428.51	161.42	28.19	100.68	3705.65	3808.60
q15	***		***	-	258.52	531.02	315.25	54.06	227.81	3834.95	3904.52
q16	***			***	-	548.93	253.40	37.43	160.28	3793.81	3928.16
q17	***	***	***	***	***	-	994.05	570.43	568.14	4217.64	4122.83
q18	***	***	***	***	***	***	-	210.44	365.85	3905.79	3971.47
q19	***			***	***	***	***	-	478.93	3841.25	3835.83
q20	***		***	***	***	***	***	***	-	5792.59	4080.93
q21	***	***	***	***	***	***	***	***	***	-	21288.92
q22	***	***	***	***	***	***	***	***	***	***	-

'***' denotes pairs of items with lack-of-fit

Table 9

Fit of the Item Response Theory on Questions 12-22 without constraint

Fit on the Two-Way Margins

	q12	q13	q14	q15	q16	q17	q18	q19	q20	q21	q22
q12	-	451.38	229.92	75.35	52.16	81.29	67.05	460.06	75.84	127.68	134.33
q13	***	-	35.61	30.94	93.21	69.37	162.14	552.99	15.98	62.18	57.93
q14	***		-	38.64	91.27	130.52	112.26	502.07	29.71	32.61	47.15
q15				-	135.68	91.77	136.43	1673.27	44.58	190.34	171.46
q16					-	167.89	359.72	1084.56	88.98	152.63	173.93
q17						-	1468.52	1064.50	86.25	110.70	120.47
q18		***			***	***	-	1035.36	177.78	158.13	164.30
q19	***	***	***	***	***	***	***	-	7552.78	5827.03	2922.28
q20							***	***	-	2740.03	169.58
q21	***			***				***	***	-	4133.34
q22	***			***	***			***	***	***	-

'***' denotes pairs of items with lack-of-fit

Table 10

Summary of Item Response Theory on Questions 23-29 without constraint

Question 23	Question 24	Question 25	Question 26	Question 27	Question 28	Question 29
Extrmt1 -1.629	Extrmt1 -2.081	Extrmt1 -0.279	Extrmt1 -0.911	Extrmt1 -1.188	Extrmt1 -1.720	Extrmt1 -1.551
Dscrmn 0.955	Dscrmn 0.983	Dscrmn 2.101	Dscrmn 2.899	Dscrmn 3.098	Extrmt2 -2.085	Extrmt2 -1.780
					Extrmt3 -2.871	Dscrmn -3.743
					Extrmt4 -2.944	
					Dscrmn -3.343	

Integration:

method: Gauss-Hermite

quadrature points: 21

Optimization:

Convergence: 0

max(|grad|): 92

quasi-Newton: BFGS

Table 11

Summary of Item Response Theory on Questions 23-29 with constraint

Question 23	Question 24	Question 25	Question 26	Question 27	Question 28	Question 29
Extrmt1 -2.011	Extrmt1 -2.438	Extrmt1 -0.685	Extrmt1 -1.997	Extrmt1 -2.327	Extrmt1 3.335	Extrmt1 3.331
Dscrmn 0.793	Dscrmn 0.793	Dscrmn 0.793	Dscrmn 0.793	Dscrmn 0.793	Extrmt2 4.403	Extrmt2 3.724
					Extrmt3 6.262	Dscrmn 0.793
					Extrmt4 7.120	
					Dscrmn 0.793	

Integration:

method: Gauss-Hermite

quadrature points: 21

Optimization:

Convergence: 0

max(|grad|): 0.056

quasi-Newton: BFGS

Table 12

Summary of 3 factor analysis maximum-likelihood without rotation

	Q 12	Q 13	Q 14	Q 15	Q 16	Q 17	Q 18	Q 19	Q 20	Q 21	Q 22	Q 23	Q 24	Q 25	Q 26	Q 27	Q 28	Q 29
Uniqueness	0.815	0.868	0.810	0.908	0.770	0.468	0.460	0.834	0.607	0.005	0.449	0.910	0.909	0.840	0.601	0.619	0.198	0.153
Factor 1	0.109	0.111		0.177	0.189	0.186	0.178	-0.238	0.173			-0.241	-0.223	-0.364	-0.609	-0.595	0.864	0.889

Factor 2	0.108	0.100	0.115	0.156	0.180	0.157	0.159	-0.323	0.595	0.997	0.734	-0.136	-0.185	-0.166	-0.164	-0.161	0.236	0.193
Factor 3	0.402	0.331	0.413	0.191	0.402	0.688	0.695					-0.115						-0.142

Factor1 Factor2 Factor3

SS loadings 2.756 2.359 1.662

Proportion Var 0.153 0.131 0.092

Cumulative Var 0.153 0.284 0.377

Test of the hypothesis that 3 factors are sufficient.

The chi square statistic is 8963.69 on 102 degrees of freedom.

The p-value is 0

Table 13

Summary of 4 factor analysis maximum-likelihood without rotation

	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26	Q27	Q28	Q29
Uniqueness	0.817	0.870	0.808	0.898	0.770	0.462	0.450	0.816	0.596	0.005	0.448	0.850	0.855	0.652	0.303	0.399	0.005	0.251
Factor 1	0.140	0.144	0.145	0.218	0.259	0.215	0.227	-0.377	0.554	0.770	0.609	0.215	-0.246	0.295	-0.432	-0.431	0.789	0.664
Factor 2	0.288	0.230	0.242	0.227	0.308	0.504	0.461	-0.189	0.171	0.634	0.413	0.300	-0.264	0.370	0.465	0.416	0.610	0.524
Factor 3									0.259	0.634	0.413			0.104	0.281	0.284	-0.610	-0.524
Factor 4	0.284	0.236	0.336		0.259	0.488	0.533					0.108	0.120	0.338	0.464	0.401		-0.178

Factor1 Factor2 Factor3 Factor4

SS loadings 3.317 1.565 1.465 1.399

Proportion Var 0.184 0.087 0.081 0.078

Cumulative Var 0.184 0.271 0.353 0.430

Test of the hypothesis that 4 factors are sufficient.

The chi square statistic is 5104.65 on 87 degrees of freedom.

The p-value is 0

Table 14

Display of the code of Loadings of Principal Component Analysis

Loadings:													
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13
q12	0.452	0.445	0.722				0.102			0.109		0.187	
q13	0.120		0.139					0.275	-0.160	-0.482	-0.165	-0.765	
q14	0.174	0.103			-0.134		-0.491	-0.800		-0.122		-0.173	
q15	0.100			0.130	-0.235	0.102	0.385	-0.250	-0.798	0.196	-0.111		
q16	0.234			0.140	-0.848	-0.209		0.166	0.274	0.193	-0.112		
q17	0.610	0.307	-0.610	-0.112	0.234					0.232		-0.159	
q18	0.242		-0.209		-0.117		-0.117	0.134	-0.200	-0.708		0.540	
q19						-0.103							0.102
q20	0.219	-0.363				0.759	-0.161					-0.308	
q21	0.264	-0.506	0.137	-0.343								0.545	
q22	0.274	-0.417	0.120	-0.367		-0.530	0.105					-0.423	
q23				-0.149			-0.322		-0.126	0.126	-0.654		
q24				-0.113			-0.262		-0.107		-0.504		
q25		0.135		-0.292	-0.118		-0.410	0.327	-0.343	0.235		-0.328	
q26		0.118		-0.323	-0.116				-0.103		0.438		
q27		0.103		-0.284							0.132		0.368
q28	0.145	-0.166		0.427	0.125	-0.176	-0.329	0.135	-0.169		0.107		0.161
q29	0.110	-0.167		0.454	0.209	-0.168	-0.281	0.136	-0.123	0.121	0.104		0.163
	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18								
q12													
q13													
q14													
q15													
q16													
q17													
q18													
q19			-0.200	-0.956									
q20	-0.261			-0.158									
q21	0.470												
q22	-0.336												
q23		0.618											
q24		-0.783											
q25	0.341												
q26	-0.477		0.653	-0.116	-0.158								
q27	-0.431		-0.704	0.192									
q28	-0.201		0.118		0.685								
q29	-0.111		-0.130		-0.697								
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	
ss loadings	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
Proportion var	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	
Cumulative var	0.056	0.111	0.167	0.222	0.278	0.333	0.389	0.444	0.500	0.556	0.611	0.667	
	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18							
ss loadings	1.000	1.000	1.000	1.000	1.000	1.000							
Proportion var	0.056	0.056	0.056	0.056	0.056	0.056							
Cumulative var	0.722	0.778	0.833	0.889	0.944	1.000							

Figures

Figure 1

A visualization of the class population share of the 2 class polytomous latent classes for questions 12-22

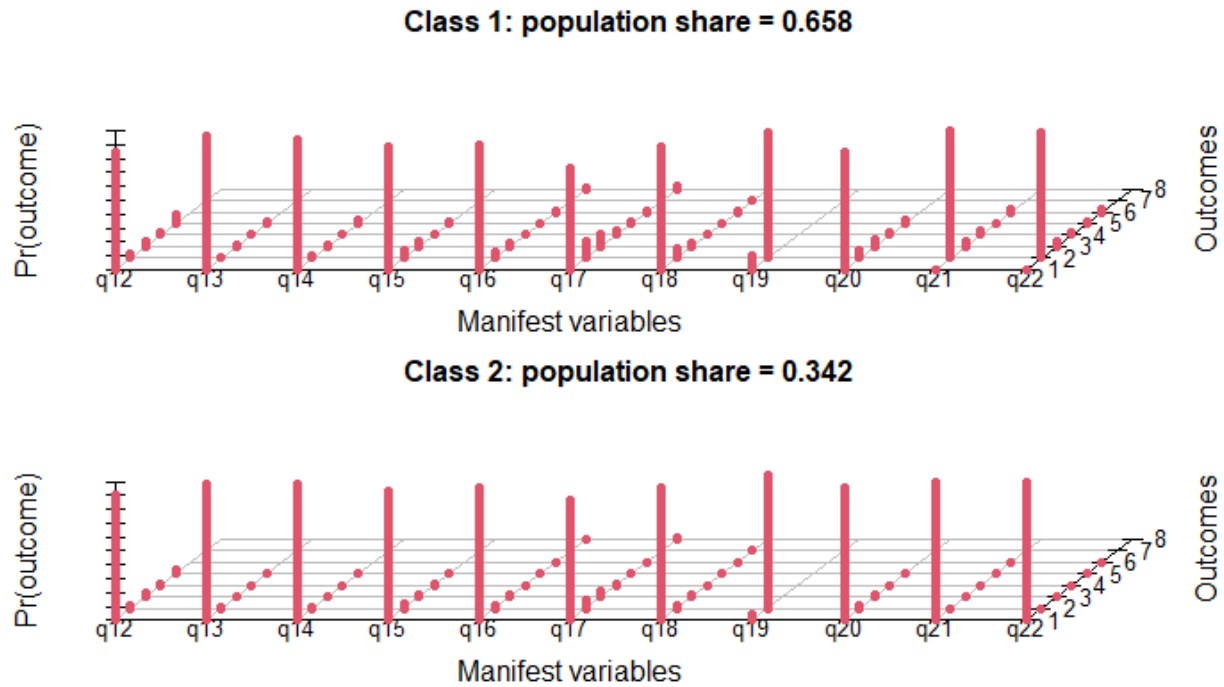
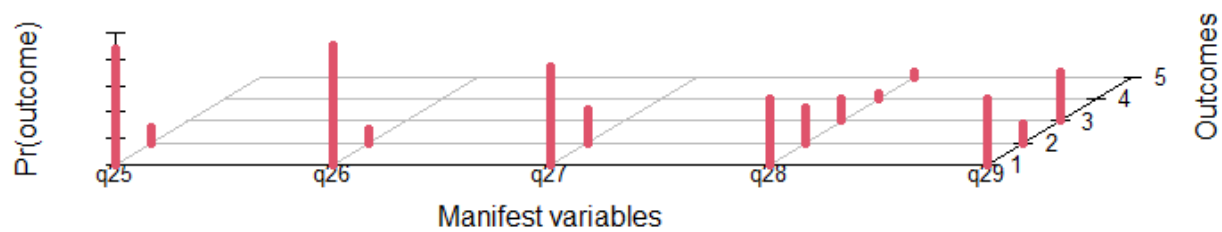


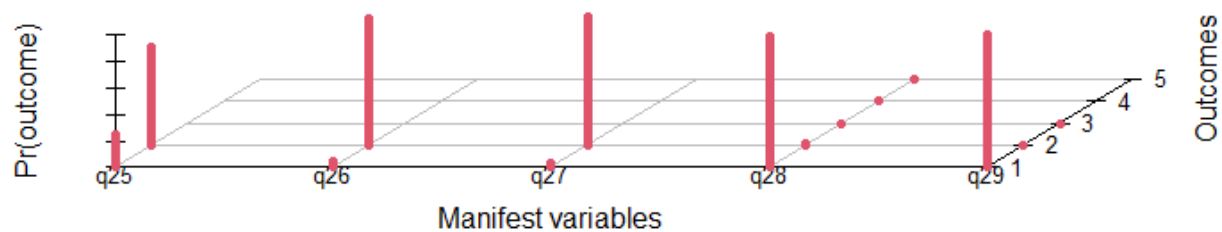
Figure 2

A visualization of the class population share of the 2 class polytomous latent classes for questions 23-29

Class 1: population share = 0.185



Class 2: population share = 0.815



Bibliography

- Alhajji, M., Bass, S., & Dai, T. (2019). Cyberbullying, Mental Health, and Violence in Adolescents and Associations With Sex and Race: Data From the 2015 Youth Risk Behavior Survey. *Global Pediatric Health*, 6. <https://doi.org/10.1177/2333794x19868887>
- Anniko, M. K., Boersma, K., & Tillfors, M. (2018). Sources of stress and worry in the development of stress-related mental health problems: A longitudinal investigation from early- to mid-adolescence. *Anxiety, Stress, & Coping*, 32(2), 155–167. <https://doi.org/10.1080/10615806.2018.1549657>
- Brener, N. D., Flint, K. H., Hawkins, J., Eaton, D. K., Kinchen, S., Shanklin, S., & Kann, L. (2013). Methodology of the Youth Risk Behavior Surveillance System — 2013. *Youth Risk Behavior Surveillance System - National High School (YRBS-NHS)*, 62(1), 1–20. <https://doi.org/http://dx.doi.org/10.15585/mmwr.mm695152a7>
- Bunston, W., Franich-Ray, C., & Tatlow, S. (2017). A Diagnosis of Denial: How Mental Health Classification Systems Have Struggled to Recognise Family Violence as a Serious Risk Factor in the Development of Mental Health Issues for Infants, Children, Adolescents and Adults. *Brain Sciences*, 7(12), 133. <https://doi.org/10.3390/brainsci7100133>
- Centers for Disease Control and Prevention. 2019 Youth Risk Behavior Survey Data. Available at: www.cdc.gov/yrbs. Accessed on May 15th, 2021.
- Centers for Disease Control and Prevention. 2019 Youth Risk Behavior Survey Questionnaire. Available at: www.cdc.gov/yrbs. Accessed on May 15th, 2021.
- Copeland-Linder, N., Lambert, S. F., & Ialongo, N. S. (2010). Community Violence, Protective Factors, and Adolescent Mental Health: A Profile Analysis. *Journal of Clinical Child & Adolescent Psychology*, 39(2), 176–186. <https://doi.org/10.1080/15374410903532601>
- Fisher, H. L., Moffitt, T. E., Houts, R. M., Belsky, D. W., Arseneault, L., & Caspi, A. (2012). Bullying victimisation and risk of self harm in early adolescence: longitudinal cohort study. *BMJ*, 344(apr26 2). <https://doi.org/10.1136/bmj.e2683>
- Gargano, L. M., Locke, S., Li, J., & Farfel, M. R. (2018). Behavior problems in adolescence and subsequent mental health in early adulthood: results from the World Trade Center Health Registry Cohort. *Pediatric Research*, 84(2), 205–209. <https://doi.org/10.1038/s41390-018-0050-8>

- Håkansson, A., & Jesionowska, V. (2018). Associations between substance use and type of crime in prisoners with substance use problems – a focus on violence and fatal violence. *Substance Abuse and Rehabilitation, Volume 9*, 1–9. <https://doi.org/10.2147/sar.s143251>
- Hanson, R. F., Borntrager, C., Self-Brown, S., Kilpatrick, D. G., Saunders, B. E., Resnick, H. S., & Amstadter, A. (2008). Relations among gender, violence exposure, and mental health: The national survey of adolescents. *American Journal of Orthopsychiatry*, 78(3), 313–321. <https://doi.org/10.1037/a0014056>
- Hecker, T., Hermenau, K., Maedl, A., Hinkel, H., Schauer, M., & Elbert, T. (2013). Does Perpetrating Violence Damage Mental Health? Differences Between Forcibly Recruited and Voluntary Combatants in DR Congo. *Journal of Traumatic Stress*, 26(1), 142–148. <https://doi.org/10.1002/jts.21770>
- Hysing, M., Askeland, K. G., La Greca, A. M., Solberg, M. E., Breivik, K., & Sivertsen, B. (2019). Bullying Involvement in Adolescence: Implications for Sleep, Mental Health, and Academic Outcomes. *Journal of Interpersonal Violence*, 088626051985340. <https://doi.org/10.1177/0886260519853409>
- Murray, A. L., Obsuth, I., Eisner, M., & Ribeaud, D. (2017). Evaluating Longitudinal Invariance in Dimensions of Mental Health Across Adolescence: An Analysis of the Social Behavior Questionnaire. *Assessment*, 26(7), 1234–1245. <https://doi.org/10.1177/1073191117721741>
- Masselink, M., Van Roekel, E., & Oldehinkel, A. J. (2017). Self-esteem in Early Adolescence as Predictor of Depressive Symptoms in Late Adolescence and Early Adulthood: The Mediating Role of Motivational and Social Factors. *Journal of Youth and Adolescence*, 47(5), 932–946. <https://doi.org/10.1007/s10964-017-0727-z>
- Odenbring, Y. (2017). Mental Health, Drug Use and Adolescence: Meeting the Needs of Vulnerable Students in Secondary School. *The Urban Review*, 50(3), 363–377. <https://doi.org/10.1007/s11256-017-0437-6>
- Odgers, C. L., & Russell, M. A. (2017). Violence exposure is associated with adolescents' same- and next-day mental health symptoms. *Journal of Child Psychology and Psychiatry*, 58(12), 1310–1318. <https://doi.org/10.1111/jcpp.12763>
- Peltonen, K., Ellonen, N., Larsen, H. B., & Helweg-Larsen, K. (2010). Parental violence and adolescent mental health. *European Child & Adolescent Psychiatry*, 19(11), 813–822. <https://doi.org/10.1007/s00787-010-0130-8>
- Stone, D. (2018). Dangerous Minds: Myths and Realities behind the Violent Behavior of the Mentally Ill, Public Perceptions, and the Judicial Response through Involuntary Civil Commitment. *Law & Psychology Review*, 42, 59–83.
- Vander Stoep, A., Adrian, M., McCauley, E., Crowell, S. E., Stone, A., & Flynn, C. (2011). Risk for suicidal ideation and suicide attempts associated with co-occurring depression and

conduct problems in early adolescence. *Suicide & Life-Threatening Behavior*, 41(3), 316–329. <https://doi.org/10.1111/j.1943-278X.2011.00031.x>

Wartberg, L., & Kammerl, R. (2020). Empirical Relationships between Problematic Alcohol Use and a Problematic Use of Video Games, Social Media and the Internet and Their Associations to Mental Health in Adolescence. *International Journal of Environmental Research and Public Health*, 17(17), 6098. <https://doi.org/10.3390/ijerph17176098>

Winding, T. N., Skouenborg, L. A., Mortensen, V. L., & Andersen, J. H. (2020). Is bullying in adolescence associated with the development of depressive symptoms in adulthood?: A longitudinal cohort study. *BMC Psychology*, 8(1). <https://doi.org/10.1186/s40359-020-00491-5>