Survey Engagement Analysis on Harvard CAS Dataset

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Abstract

Harvard SPH College Alcohol Study (CAS) collected a multi-round survey that interviewed students about their alcohol use and other high risk behaviors. The survey contains multiple Likert scale questions, and we identified that a large number of students tend to give the same answer for these similar questions, indicating that they're less engaged in the survey. To address this latent survey engagement factor, we use structual equation model (SEM) to estimate response quality and survey engagement, finding out relationships between drinking behaviors and survey engagement.

1. Introduction

Harvard CAS contains four sets of survey responses from undergraduates in four years: 1993, 1997, 1999 and 2001. The survey mainly focus on students high risk behaviors (e.g. alcohol, tobacco and illicit drugs), including other information such as students' views on campus alcohol policies, personal background variables, etc.

These four surveys each consists of over 400 questions, which could take up to an hour for a student to complete. The survey also has many similar nested questions (e.g. Fig 1). It's probable that some students are less engaged in completing the survey, finally returning the survey with non-informative responses. In psychology, these nested similar questions are called Likert scale questions. Here's a standard five point Likert scale: (1) Strongly Disagree (2) Disagree (3) Undecided (4) Agree (5) Strongly Agree. With so many Likert scale questions in a single survey, we find out that a non-negligible proportion of students tend to give the same answer for these questions.

From this perspective, we are interested in exploring the latent survey engagement factor behind students. Specifically, we are interested in (1) quantifying and estimating latent survey engagement (2) exploring relationship between drinking behaviors and survey engagement. To make our analysis more detailed, our report focuses on the 1999 survey, but it's straightforward to use our approahces to analyze other surveys.

2. Materials and Methods

Survey Engagement paper: (Hess and Stathopoulos 2013)

SEM paper: (Ullman and Bentler 2003)

Model structure hyperlink: Fig 2

Simplified model hyperlink: Fig 3

Model 1 semplot hpyerlink: Fig 4

Model 2 semplot hpyerlink: Fig 5

3. Results

3.1 Exploratory Data Analysis & Data Preprocessing

Initial data exploration suggests that some students give the same answer for nested Likert scale questions (Fig 6). We can see a large number of students response with the first Likert scale (so their sum over 10 questions are 0), implying that engagement among students varies.

The survey contains a large number of missing data, and we consider different ways to deal with it: (1) use complete cases, (2) manually impute with reasonable values for questions need not to answer, (3) use MICE (Buuren and Groothuis-Oudshoorn 2010) to impute, (4) use DPMPM (Fig 7, Dunson and Xing (2009), Si and Reiter (2013)). We will later explain our sensitivity analysis through different missing data manipulations.

Instead of analyzing all questions in the survey, which is unnecessary and redundant, we select some important questions of interest (Fig 8). Specifically speaking, for personal characteristics, we include sex, age group, comments, drink_category (from codebook), drink_occ (question C8, C9), drink_num (question C8, C10), advice (question D4), complaint (question D5), perception (D3A, D3B), etc. To further address our concern on students' view on alchohol policies, we include questions related to their attitudes (question B1, B2, B3, B4, B5). For choice indicator Y, we will focus on question B15 (Fig 1). We preprocess these variables using different criteria and formulas, which is explicitly explained in our codebook for variables of interest (Fig 8). Among quesitons of interest, around 20% cases have missing data.

3.2 Main Results

Model 1 result hpyerlink: Fig 9, 10

Model 2 result hpyerlink: Fig 11, 12

3.3 Sensitivity Analysis

About 20% cases have missing data with respect to our variables of interest (Fig 8). We consider four ways to manipulate these missing data: (1) use complete cases, (2) manually impute with reasonable values for questions no need to answer, (3) use MICE (Buuren and Groothuis-Oudshoorn 2010) to impute, (4) use nonparamatric Bayesian imputation DPMPM (Fig 7, Dunson and Xing (2009), Si and Reiter (2013)). We would expect DPMPM to have the best performance since it's designed for large-scale categorical surveys.

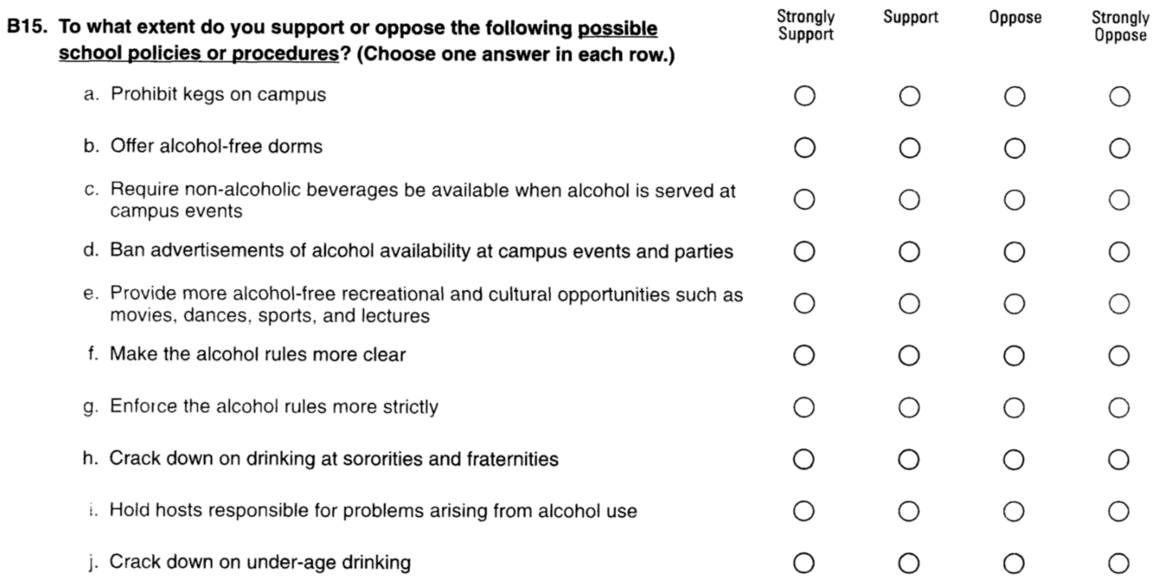
Our models using four different ways above didn't show distinguishable difference. This is probably because proportion of missing data is relatively low among questions we focus on. Therefore we choose to use the original dataset in future work, and explore missing data manipulation further.

4. Discussion

Our Structural Equation Model successfully discovers latent survey engagement factors in Havard CAS dataset. We also discover relationships between drinking behaviors and survey engagement. However, we carry out a simplified version of original model due to constraint of lavaan package (Rosseel 2012). A direct future work is to implement the model jointly. To further account for uncertainty, we may implement it using Rstan or JAGS.

To find nonlinear effects of latent factors, we may consider using autoencoder (Kramer 1991). Autoencoder can be viewed as a nonlinear factor analysis that primarily uses neural networks to first encode the input and later decode it. However, autoencoder may suffer from interpretability due to its complexity.

Another direction is to consider low-rank factorization of contingency tables. Sparse PARAFAC (@ Zhou et al. 2015) uses low rank tensor factorization together with parallel factor analysis, which is helpful when the sample size is massively less than the number of cells. This model can be further used for latent class clustering.



B15. To what extent do you support or oppose the following possible school policies or procedures? (Choose one answer in each row.)

	Strongly Support	Support	Oppose	Strongly Oppose
a. Prohibit kegs on campus	○	○	○	○
b. Offer alcohol-free dorms	○	○	○	○
c. Require non-alcoholic beverages be available when alcohol is served at campus events	○	○	○	○
d. Ban advertisements of alcohol availability at campus events and parties	○	○	○	○
e. Provide more alcohol-free recreational and cultural opportunities such as movies, dances, sports, and lectures	○	○	○	○
f. Make the alcohol rules more clear	○	○	○	○
g. Enforce the alcohol rules more strictly	○	○	○	○
h. Crack down on drinking at sororities and fraternities	○	○	○	○
i. Hold hosts responsible for problems arising from alcohol use	○	○	○	○
j. Crack down on under-age drinking	○	○	○	○

Figure 1: Question B15

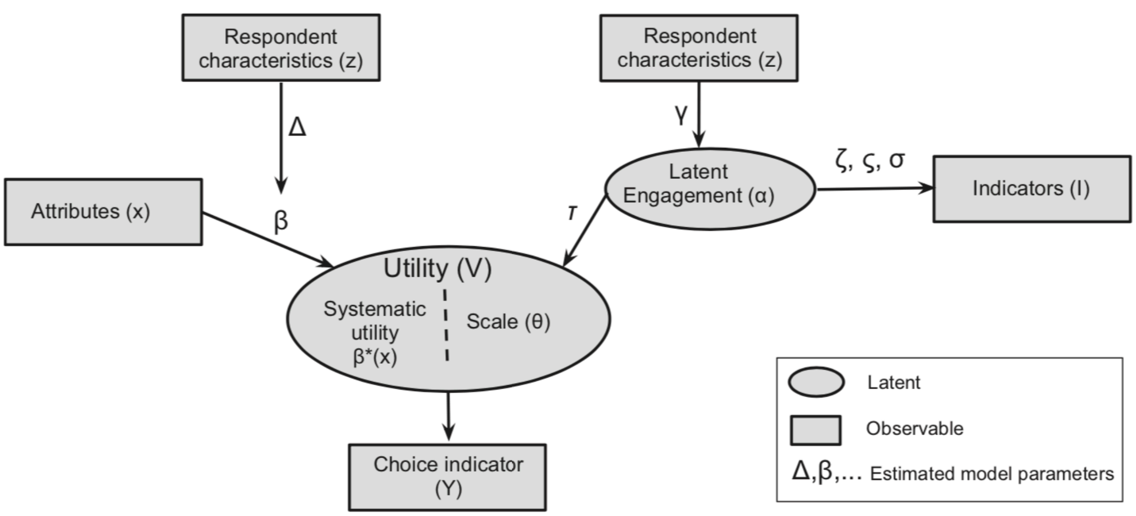


Figure 2: Model Structure

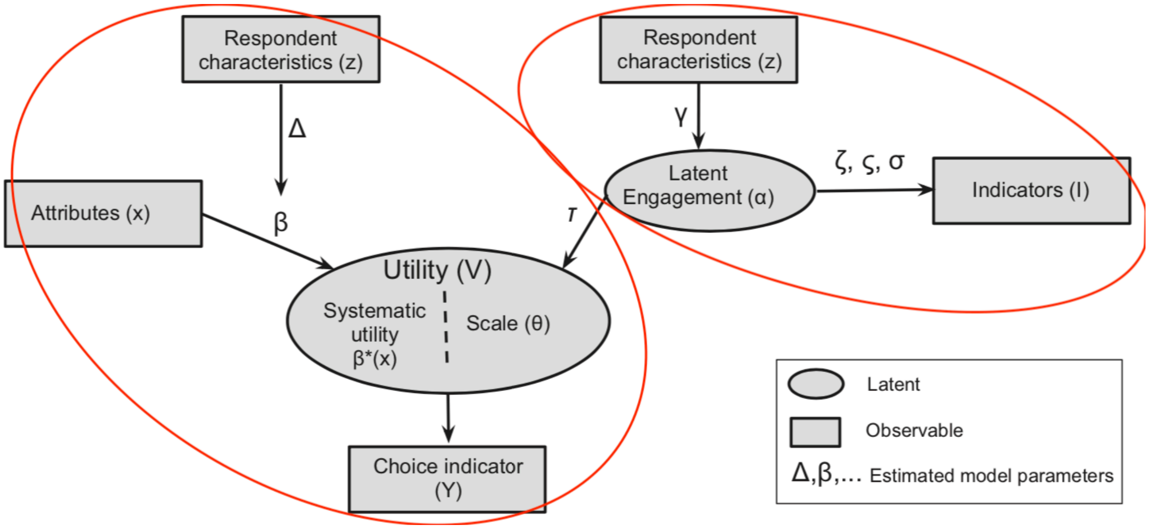


Figure 3: Simplified Model

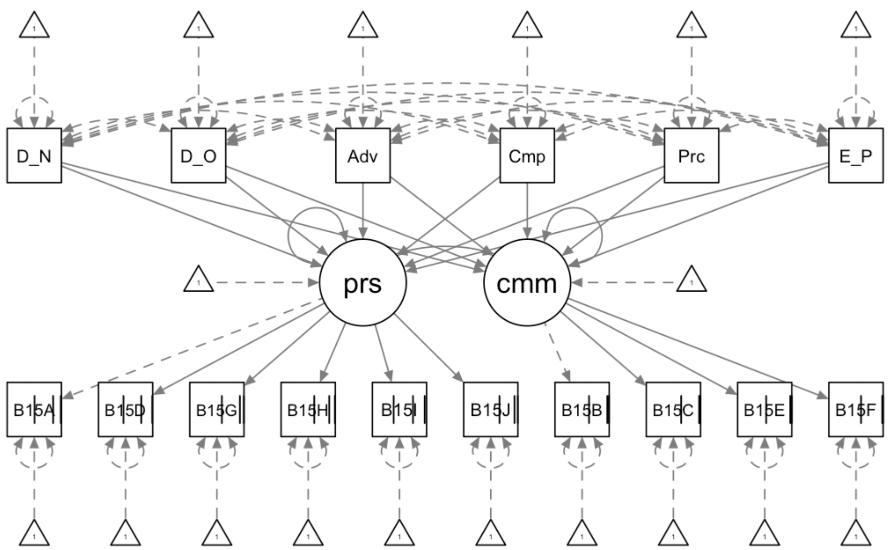


Figure 4: Model 1 SEM plot

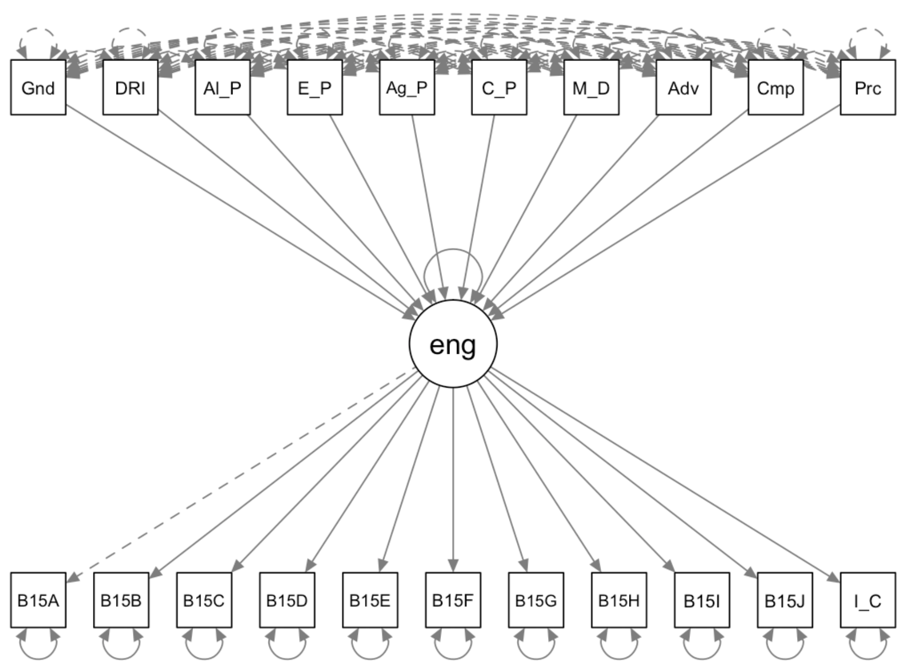


Figure 5: Model 2 SEM plot

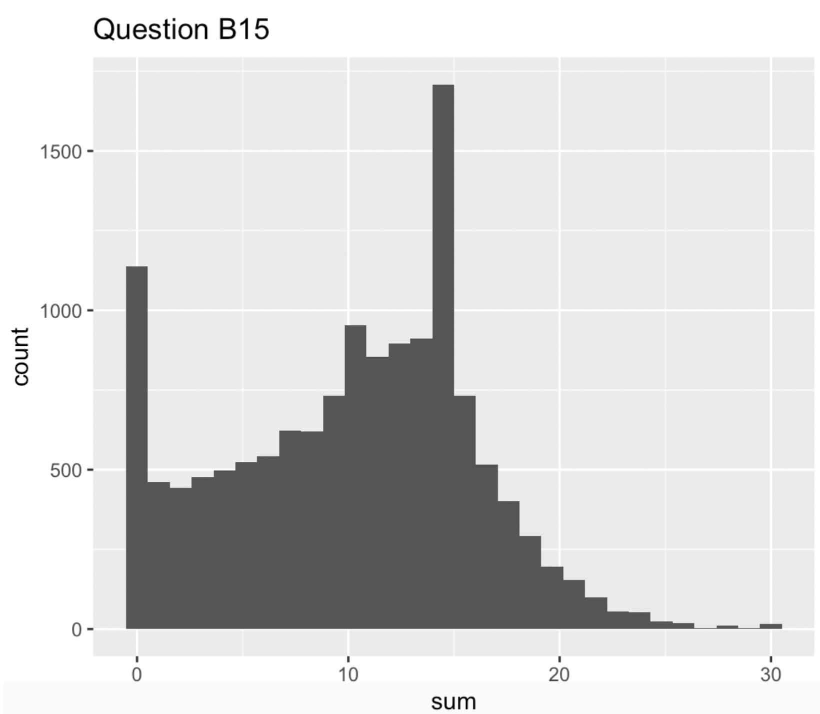


Figure 6: Histogram of sum of individual answers for question B15

$$
\begin{aligned}
X_{ij}|z_i, \phi &\sim \text{Multinomial}(\phi_{z_i, j1}, ..., \phi_{z_i jd_j}) \\
z_i \pi &\sim \text{Multinomial}(\pi_1, ..., \pi_\infty) \\
pi_h &= V_h \prod_{g<h} (1 - V_g), \quad h = 1, ..., \infty \\
V_h &\sim \text{Beta}(1, \alpha) \\
\alpha &\sim Gamma(a_\alpha, b_\alpha) \\
\phi_{hj} &= (\phi_{hj1}, ..., \phi_{hjd_j}) \sim \text{Multinomial}(a_{j1}, ..., a_{jd_j})
\end{aligned}
$$

Figure 7: Infinite Mixture of Product of Multinomials

Ind_Comment	COMMENTS	1 (yes); 2 (no)	1 (yes); 0 (no)
Gender	SEX	0 (female); 1 (male)	-
Age_Group	AGEGROUP	1: <21; 2: 21-23; 3: >23	1: <21; 0: >=21
DRINKCAT	DRINKCAT	1,2,3 (codebook)	-
Alc_Problem	B1	1:major; 2:minor; 3:yes; 4: no	1: yes; 0: no
AP_all	B2	1 (all)	1: yes; 0: no
AP_stu	B2	2 (all students)	1: yes; 0: no
AP_all21	B2	3 (all <21)	1: yes; 0: no
AP_stu21	B2	4 (all student <21)	1: yes; 0: no
AP_no	B2	5 (no policy)	1: yes; 0: no
AP_notknow	B2	6 (don't know)	1: yes; 0: no
Enforce_Pol	B3	1-3: enforced; 4-5: not enforced/don't know	1: enforced; 0: no
Agree_Pol	B4	1-2: agree; 3-4: disagree	1: agree; 0: disagree
Change_Pol	B5	2-3: change; 1: not change; 4: don't know	1: change; 0: others
Min_Drink_Age	B13	1-4: below 21; 5: 21	1: <21; 0: 21
Drink_Occ	C8, C9	C9=1: none<=30days; 2-7; C8:1,2,3: no drink<=30days	If C8=1,2,3 -> Drink_Occ=1; else follow C9
Drink_Num	C8, C10	C10=0: none<=30days; 1-9; C8:1,2,3: no drink<=30days	If C8=1,2,3 -> Drink_Num=0; else follow C10
Advice	D4	1,2,3,4	1 (no), 2,3,4
Complaint	D5	1,2,3,4	1 (no), 2,3,4
Perception	D3A, D3B	D3A: All students; D3B: Your friends	D3B/D3A

Figure 8: Variables of Interest

Latent Variables:

	Estimate	Std.Err	z-value	P(>|z|)
personal =~				
B15A	1.000			
B15D	1.023	0.013	81.215	0.000
B15G	1.408	0.014	99.281	0.000
B15H	1.204	0.013	93.422	0.000
B15I	0.932	0.013	73.739	0.000
B15J	1.314	0.013	97.315	0.000
communal =~				
B15B	1.000			
B15C	0.879	0.016	53.845	0.000
B15E	1.082	0.016	67.255	0.000
B15F	1.218	0.018	67.855	0.000

Figure 9: Model 1 Latent Factors

Regressions:

	Estimate	Std.Err	z-value	P(>|z|)
personal ~				
Drink_Num	0.080	0.004	22.805	0.000
Drink_Occ	0.188	0.006	30.606	0.000
Advice	0.024	0.007	3.607	0.000
Complaint	-0.145	0.014	-10.081	0.000
Perception	0.144	0.012	12.484	0.000
Enforce_Pol	0.044	0.017	2.638	0.008
communal ~				
Drink_Num	0.061	0.004	14.955	0.000
Drink_Occ	0.142	0.007	20.209	0.000
Advice	-0.023	0.007	-3.044	0.002
Complaint	-0.098	0.016	-5.992	0.000
Perception	0.092	0.014	6.563	0.000
Enforce_Pol	0.009	0.019	0.485	0.627

Figure 10: Model 1 Regression results

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)
  engagement =~
    B15A_Res2         0.021    0.004    5.466    0.000
    B15B_Res2         0.083    0.003   24.244    0.000
    B15C_Res2         0.111    0.003   31.970    0.000
    B15D_Res2         0.038    0.004   10.173    0.000
    B15E_Res2         0.126    0.003   39.163    0.000
    B15F_Res2         0.187    0.004   51.104    0.000
    B15G_Res2         0.180    0.004   51.213    0.000
    B15H_Res2         0.053    0.003   16.390    0.000
    B15I_Res2         0.020    0.004    4.835    0.000
    B15J_Res2         0.121    0.003   37.507    0.000
    Ind_Comment       0.004    0.003    1.330    0.183
```

Figure 11: Model 2 Latent Factors

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  engagement ~
    Gender           -0.292    0.030   -9.593    0.000
    DRINKCAT         -0.961    0.023  -42.539    0.000
    Alc_Problem       0.330    0.040    8.288    0.000
    Enforce_Pol       0.044    0.037    1.197    0.231
    Agree_Pol         0.063    0.037    1.727    0.084
    Change_Pol        0.162    0.036    4.566    0.000
    Min_Drink_Age    -1.090    0.036  -30.471    0.000
    Advice           -0.002    0.015   -0.164    0.869
    Complaint         0.416    0.033   12.742    0.000
    Perception       -0.349    0.030  -11.721    0.000
```

Figure 12: Model 2 Regression results

References

Buuren, S van, and Karin Groothuis-Oudshoorn. 2010. "Mice: Multivariate Imputation by Chained Equations in R." *Journal of Statistical Software*. University of California, Los Angeles, 1–68.

Dunson, David B, and Chuanhua Xing. 2009. "Nonparametric Bayes Modeling of Multivariate Categorical Data." *Journal of the American Statistical Association* 104 (487). Taylor & Francis: 1042–51.

Hess, Stephane, and Amanda Stathopoulos. 2013. "Linking Response Quality to Survey Engagement: A Combined Random Scale and Latent Variable Approach." *Journal of Choice Modelling* 7. Elsevier:

1–12.

Kramer, Mark A. 1991. “Nonlinear Principal Component Analysis Using Autoassociative Neural Networks.” *AIChE Journal* 37 (2). Wiley Online Library: 233–43.

Rosseel, Yves. 2012. “Lavaan: An R Package for Structural Equation Modeling and More. Version 0.5–12 (Beta).” *Journal of Statistical Software* 48 (2): 1–36.

Si, Yajuan, and Jerome P Reiter. 2013. “Nonparametric Bayesian Multiple Imputation for Incomplete Categorical Variables in Large-Scale Assessment Surveys.” *Journal of Educational and Behavioral Statistics* 38 (5). Sage Publications Sage CA: Los Angeles, CA: 499–521.

Ullman, Jodie B, and Peter M Bentler. 2003. “Structural Equation Modeling.” *Handbook of Psychology*. Wiley Online Library, 607–34.

Zhou, Jing, Anirban Bhattacharya, Amy H Herring, and David B Dunson. 2015. “Bayesian Factorizations of Big Sparse Tensors.” *Journal of the American Statistical Association* 110 (512). Taylor & Francis: 1562–76.