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 2). 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 relationships between drinking behaviors and survey engagement. To make our analysis more detailed, our report focuses on section B15, which explores student attitudes towards a variety of alcohol-related policies on campus, in the 1999 survey. However, it is straightforward to use our approaches to analyze other questions and surveys.

2. Materials and Methods

The philosophy behind our method is derived from "Linking response quality to survey engagement: A combined random scale and latent variable approach" (Hess and Stathopoulos 2013, Fig 1). This paper suggests modeling survey engagement as a latent multiplicative effect nestled in a larger structural equation model (SEM) (Ullman and Bentler 2003), essentially posotulating that engagement can be thought of as individualized heteroskedasticity. If an individual is not actively interested in the survey, then the data is likely to only contain a muted signal of their true preferences and vice-versa. Consequently, the model can be thought of in two parts. One SEM describing the structure of the mean response to the survey questions and another capturing the latent engagement variable that scales this mean response for an individual. However, implementing the exact model described in the Hess and Stathopoulus paper involves interacting latent variables, which can often be messy and non-intuitive in a frequentist context. Consequently, we divide the model into its two natural subparts (Fig. 3).

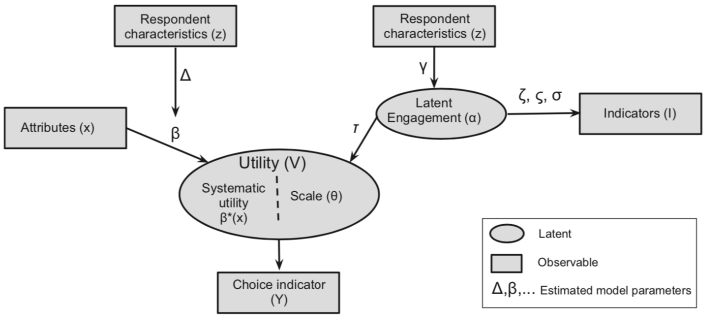

Figure 1: Model Structure

Since section B15 seems to naturally divide into questions about policies cracking down on personal alcohol use and questions about general changes to alcohol-related campus culture, we use two latent variables to capture this structure. These latent variables are then regressed on a series of personal characterstics (Fig 4). After modeling the mean survey using this SEM, we take the absolute value of the residuals (squaring them exacerbated the right skew of the residuals) from the predictions of individualized survey responses as an indication of the engagement related heteroskedacity not captured by the mean response model. We then load these residuals on an engagement variable that is in turn regressed on a series of personal characteristics (Fig 5) in a seperate SEM. We believe that this process accurately captures the latent engagement multiplicative effect in a two step modeling process.

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 2). 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

We have built two SEM to study the engagement of survey respondents. The results of the first model are presented in Fig 9 and Fig 10. As shown in Fig 9, all p-values are small, suggesting the latent indicators are all significant. In terms of magnitude, question B15(f) has the highest factor loading on latent variable `communal` and B15(c) has the lowest loading. This shows that for respondents who care about general changes of campus alcohol use have stronger opinion in "making alcohol rules more clear" than serving

non-alcohol drinks at campus events. Similarly, the factor loading on latent variable `personal` is the highest for B15(g) and is the lowest for B15(i). The respondents who care more about personal alcohol use tend to pay more attention to the enforcement of alcohol rules, rather than the responsibility of hosts regarding problematic alcohol use. The regression coefficients with standard errors are summarized in Fig 10. The enforcement of current alcohol policies has significant impact on personal awareness but not communal awareness of alcohol use. Drinking habits (including occations and numbers of alcohols taken within 30 days) and perception of proportion of binge drinkers among friends have positive influence on both personal and communal awareness. Those who have complained about drinking behaviours of fellow students also have higher personal and communal awareness. One interesting finding is that those who have asked someone to stop drinking before have higher communal awareness of campus alcohol use, but lower personal awareness. It also interesting to note that the magnitudes of all the coefficients in the communal latent factor regression are less than their counterparts relating to the personal latent factor. This somewhat intuitively suggests that personal characteristics are not as indicative of preferences affecting communal campus culture and activities.

In the second model, we analyzed individual engagement in this survey. The results are presented in Fig 11 and Fig 12. According to Fig 11, the engagement in the survey does not seem to have significant impact on leaving comments for the survey. But other than that, the variation in their responses (measured by the absolute values of residuals from the first model) are affected by their engagement in the survey. If the respondents are more engaged, their answers to these questions tend to relflect a stronger signal of their preferences. As shown in Fig 12, the following characteristics are found to have significant impact on engagement: Males seem to be less engaged than females in this survey. Respondents who drink more or have more friends who are binge drinkers are less engaged. Respondents who think legal drinking age should be below 21 are also less engaged. Those who have complained about improper behaviours before, or have desire to change current campus alcohol policies are more engaged than others.

The above results suggest that personal drinking habits, attitudes towards alcohol policies as well as the drinking behaviours of friends all have an impact on the engagement of the respondents.

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 explores 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.

Appendix

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 2: Question B15

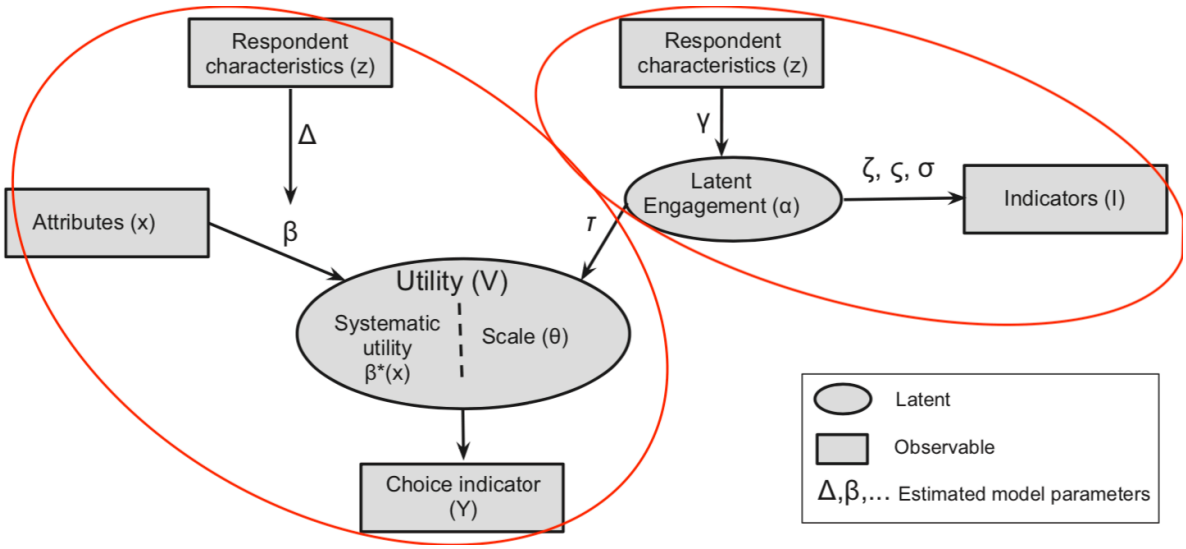

Figure 3: Simplified Model

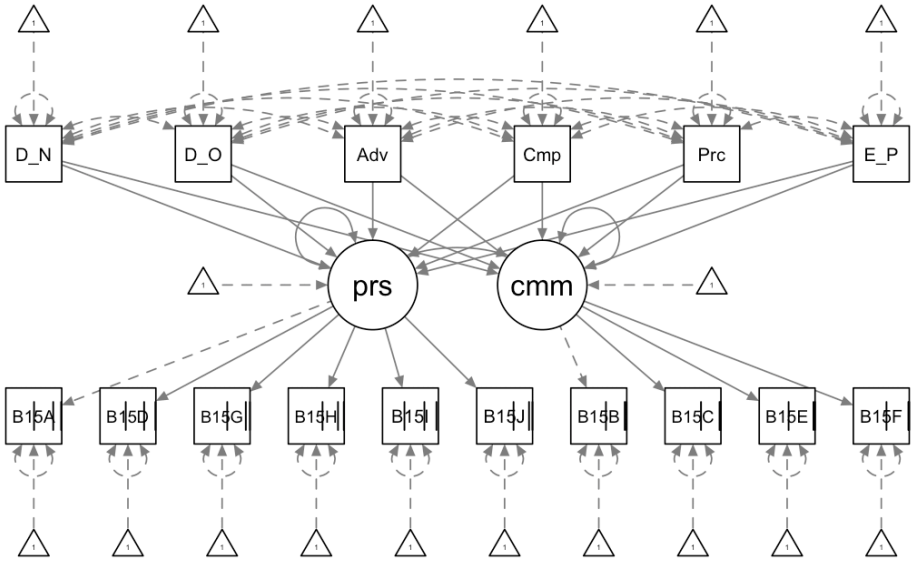

Figure 4: Model 1 SEM plot

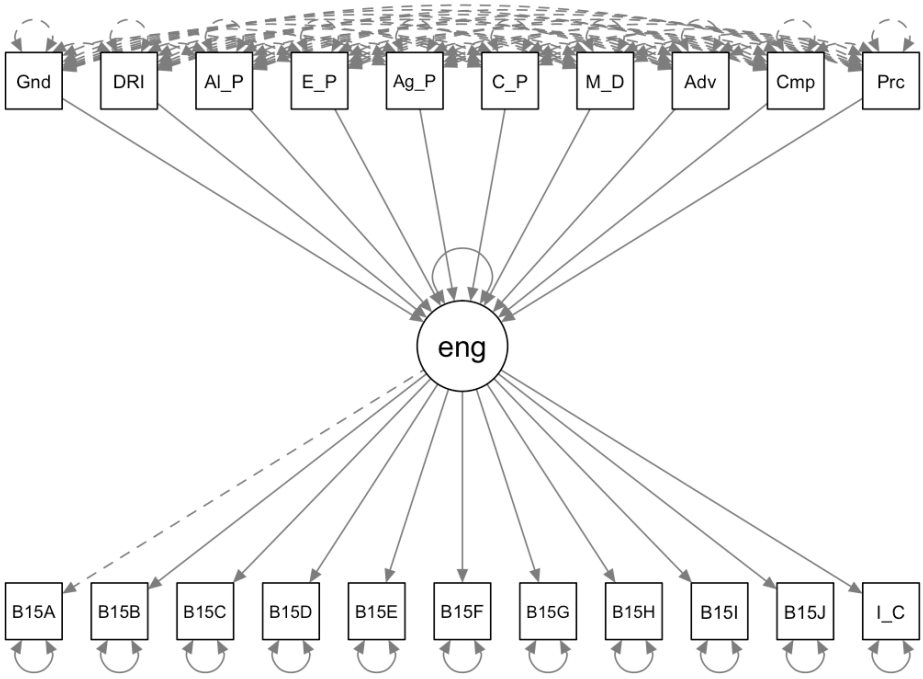

Figure 5: Model 2 SEM plot

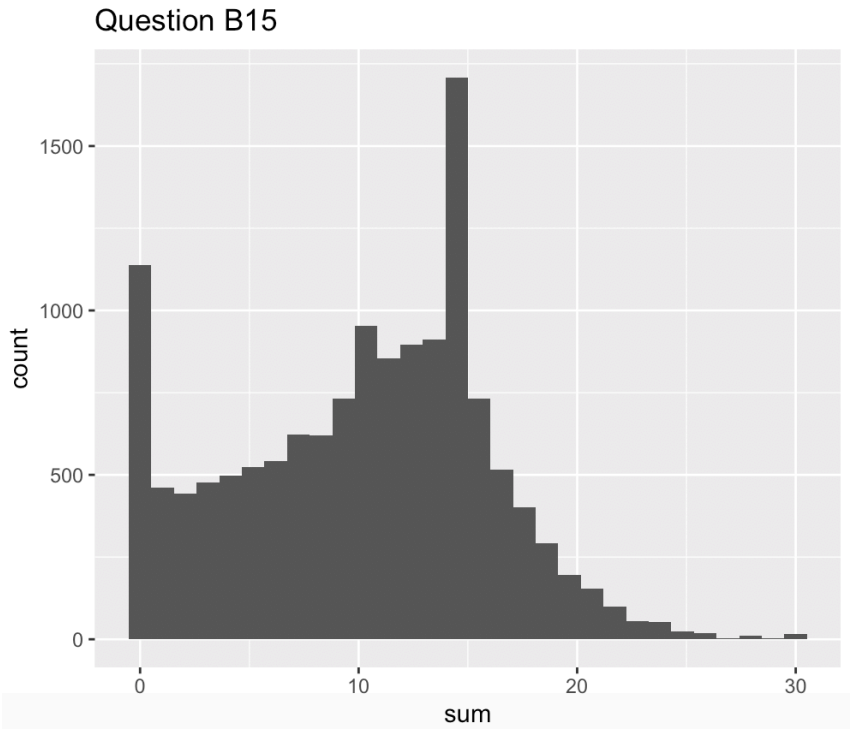

Figure 6: Histogram of sum of individual answers for question B15

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

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

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