Two-Wave Online Survey and Negative Binomial Regression: Using Optimal Methods and Statistics in a Binge-Drinking Study

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Abstract

In this case study, I describe the procedure of conducting a binge-drinking study using a two-wave online survey and a negative binomial regression, taking readers to the heart of some methodological and analytical issues that arose during the research process. It sheds light on the particular challenges of correctly applying the theory of planned behavior and using a prospective and more precise measure of the behavioral outcome. In recounting my research process, I have paid particular attention to the use of the two-wave online survey and why I decided it was the optimal method for testing the TPB model, as well as the use of the negative binomial regression and why it is the most appropriate analytical technique for count data. Such practices have made the results of this study more credible and its causal inferences more persuasive. By adopting these practices, I improved the overall quality of the study, and thus its contributions to empirical research on binge-drinking are more significant. This case study will assist student researchers in selecting the most appropriate methods and statistical techniques, dealing with methodological challenges involved in a two-wave survey, and mitigating potential weaknesses, when designing and conducting their own research.

Learning Outcomes

By the end of this case, students should be able to

- Understand the flaws of cross-sectional designs in studies applying theory of planned behavior (TPB)
- Understand the advantages of using a two-wave survey design for TPB studies and the difference between a two-wave design and a longitudinal design
- Understand how to use a theory-driven approach in designing a study
- Deal with the methodological challenges involved in using a two-wave online survey, such as creating behavioral measures consistent with conceptual definitions, merging datasets, and data cleaning
- Choose the most appropriate analysis technique for different types of outcome variable (e.g., continuous data, dichotomous data, and count data)
- Use the practical lessons illustrated by this case study to design and conduct their own research and mitigate potential weaknesses

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Project Context and Overview

I had been a teaching assistant for 4 years in the Department of Communication at the University at Buffalo, the State University of New York, USA, before I started this binge-drinking study as my dissertation. Through interactions with my students inside and outside classroom, I noticed that many of them engaged in heavy drinking, which often led to absence from classes and poor academic performance. Another issue I found among my students was that a large percentage of them seemed to be stressed out by the need to balance their time among course work, part-time jobs, and family or relationship commitments. Despite widespread anti-binge-drinking ads in the mass media and here and there on campus, those students seemed not to recognize the negative impact of binge drinking. Despite the advice offered by those ads, they seemed to keep on binge drinking, which often placed them in risky or troublesome situations. I was curious to find out what might explain binge drinking behaviors other than rational assessment—that is, cognitive factors that were regularly considered in the existing binge-drinking literature. That curiosity resulted in my decision to conduct a binge-drinking study among college students for my dissertation.

When I embarked on this study in summer 2013, most extant studies had utilized a cross-sectional design which assessed predictors and the behavioral outcome at the same time point. I also noticed that, although there were a variety of measures of binge-drinking behaviors in the literature, they did not accurately reflect the National Institute on Alcohol Abuse and Alcoholism's (NIAAA, 2004) definition, which characterizes binge drinking as having *five or more* drinks for males and having *four or more* drinks for females in about 2 hr. I reasoned that the NIAAA's definition should be more authoritative than others, as the NIAAA is a national leader in alcohol-related research and the largest funder of alcohol research in the world (NIAAA, 2016). Thus, I had determined two specific ways that my study could improve upon the method of previous studies:

1. The behavioral outcome should be measured sometime after predictors are assessed;
2. The measure of binge-drinking behavior should be consistent with the NIAAA's definition.

I designed the survey questionnaire over the summer of 2013 and submitted my Institutional Review Board (IRB) proposal at the beginning of the Fall semester. After the IRB proposal was approved, I contacted the instructor of the Introduction to Communication (COM101) class at the University at Buffalo, and then went to his class and made the announcement of my study. His class had two sections with about 250 students in each session. In my announcement, I cautioned the student participants that this would be a two-wave survey and that they would be required to fill out the first survey in 48 hr and the second survey in another 48-hr period 2 weeks later. The instructor posted the link to the first survey on the course website that day, and 2 weeks later he posted the link to the second survey. The first survey returned with 288 responses, whereas the second returned with 212 responses.

I performed a data cleaning and found that 279 responses were valid for completing the first survey, and 179 responses were valid for completing both the first and the second surveys. Then I merged the first and the second surveys together to create a new dataset. After confirming with a power analysis that a sample size of 179 would have sufficient power, I proceeded with my analysis of these 179 cases.

When plotting histograms of all variables, I noticed that the histogram of the outcome variable (i.e., binge-drinking behavior) showed a highly negatively skewed distribution. I did a natural-log transformation, but found it did not improve the normality of the outcome variable. Thus, I coded the outcome variable as a dichotomous variable and conducted a logistical regression to test the effects of predictors on the outcome variable.

In the following sections, I discuss the research design for this study, practical issues that arose during research, and practical lessons learned during the research process. This case study will help student researchers understand how I made each choice in conducting this binge-drinking study and assist them in selecting the most appropriate methods and statistical techniques when doing their own research. By learning from this case study, student researchers will gain a better insight into the process of research design and learn how to deal with methodological challenges involved in a two-wave survey. In addition, the practical lessons illustrated by this case study would be informative for student researchers in designing and conducting their own research and mitigating potential weaknesses.

Research Design

Why Is a Cross-Sectional Design Flawed for Testing TPB?

After I decided on the topic for my dissertation, I began to search for a theory that could guide my data collection process—after all, "There is nothing so practical as a good theory" (Lewin, 1951, p. 169). The theory of planned behavior (TPB) caught my attention, as it has been widely used in studies of health/risky behaviors, including binge drinking. A central tenet of TPB is that attitude, subjective norm, and perceived behavioral control predict intention, which subsequently predicts *future* behavior (Ajzen, 1991). But, by measuring antecedents (e.g., attitude, subjective norm, perceived behavioral control) and the behavioral outcome at the same time point, the theory we are actually testing is that these antecedents predict *past* behavior, as the behavior measured would be the previous behavior recalled by participants. Although past behavior can reflect future behavior to some extent, measuring past behavior as a proxy of future behavior does *not* correctly reflect the TPB. As such, all studies applying the TPB model and using a cross-sectional design are methodologically flawed.

Why a Two-Wave Survey and Is It Longitudinal?

After I ruled out a cross-sectional design for my study, I faced two choices: I can either do a more rigorous longitudinal design (measuring antecedents together with the behavioral outcome at several different time points) or a simpler two-wave design (measuring antecedents at one time point and the behavioral outcome at a later time point). I chose the latter for two reasons:

1. The longitudinal design, although more rigorous, would also require a longer time in data collection. I needed to make sure I had sufficient time for data analyses and the writing of my dissertation.
2. The only incentive I could provide participants was extra credit for the introductory communication class they were taking.

I was concerned that, if the second-wave survey were exactly the same as the first-wave survey, participants would not be willing to complete it, or they would get bored when doing it. By contrast, if the second-wave survey contained only a brief four-question assessment of drinking behavior in the past, perhaps participants would be more likely to finish it.

Originally, I thought that this sort of two-wave design *was* one kind of longitudinal study. Unfortunately, I was not able to find any academic publication to back up this claim. I consulted my dissertation advisor, committee members, and some senior scholars in communication and psychology, and their opinions differed. Some told me this was not longitudinal, as I did not have *repeated* measures of antecedents and the behavioral outcome. Some told me that this was longitudinal, as the behavioral outcome was measured some time *after* antecedents were measured. Others told me that this would be a longitudinal study, if I added *past* behavior as an additional control variable. To avoid contention, I decided to call this study a two-wave survey.

Time Frame Between Wave 1 and Wave 2 Surveys

After I decided on conducting a two-wave survey, I needed to decide how much time should pass between the first survey (which would measure all predictors) and the second (which would measure the binge-drinking behavior). I decided that a 2-week time frame was an appropriate choice, as it has been used by previous studies (e.g., Elliott & Ainsworth, 2012). In addition, my study involved the impacts of stress and loneliness, two affective factors, on binge-drinking behavior. Using a 2-week time frame perhaps would be more likely to detect the consequences of those affective factors than would a longer time frame, as college students' stress and loneliness levels may vary during a semester.

Some researchers may argue that a 2-week time frame between Wave 1 and Wave 2 is too short, and that this is a weakness of the study.[1] I would like to emphasize that a prospective measure of binge-drinking behavior represents an improvement in the study design, considering over half of published TPB studies utilized cross-sectional designs (Elliott & Ainsworth, 2012). Although some alternative explanations (e.g., risk perception) cannot be ruled out (Chen, 2017; Chen & Yang, 2015), using a two-wave online survey makes the causal claims in the study stronger, as all predictors preceded the outcome variable. Thus, it should be considered a strength of the study rather than a weakness.

Should Past Drinking Behavior Be Included as a Control?

If you reviewed publications on binge drinking, you would notice that some included past drinking behavior as one of the predictors/control variables, whereas others did not. In my case, I excluded past drinking behavior in the study. Is this a flaw of the study?[2] I don’t think so for two reasons. First, the variables incorporated into the proposed model in the study are based on two theoretical frameworks (the TPB and the stress-coping hypothesis), representing the theory-driven approach. Neither the TPB nor the stress-coping hypothesis includes past behavior as a predictor of future behavior. Second, Susan Collins and Kate Carey (2007), through a confirmatory test of the TPB model in predicting binge drinking, demonstrated that a TPB model without past drinking behavior supplies a better fit than a model which includes it. In sum, with the theory-driven approach in mind and in the interests of parsimony, I believe it is more appropriate not to include past drinking behavior as a predictor/control variable in the proposed model.

Research Practicalities

Sample

During my doctoral study, I had conducted research by using national sample datasets, which was a fruitful endeavor: I already had three publications in reputable journals (Chen & Feeley, 2012, 2014a, 2014b), before I defended my dissertation proposal. Using national sample datasets has many advantages: the samples are usually representative of the population, and the findings are more generalizable. One of the major downsides of using such datasets is that the dataset might not have measured the variables one is interested in, or that these variables were measured by only one or two items, which could incur a higher measurement error (Chen & Feeley, 2014a; Chen & Yang, 2017).

I explored some national sample datasets involving young adults’ drinking behaviors, but I did not find one that had measured all the variables that I intended to study. So I decided to collect my own data among undergraduate students taking an introductory communication course at the University at Buffalo. Using a convenience sample such as this makes the findings not generalizable, but it allows you to design a study with exactly the variables you need, carefully and appropriately operationalized to match their conceptual definitions.

Measuring Binge-Drinking Behavior

When I searched for appropriate measures of binge-drinking behavior, I found that no extant measures precisely reflected the NIAAA's definition. As noted earlier, the NIAAA's definition characterizes binge drinking as having *five or more* drinks for males and having *four or more* drinks for females in about 2 hr. Some researchers used the same five-drink standard to identify binge drinkers, neglecting the gender-difference in criteria (e.g., Johnston & White, 2003). Others asked participants how often/whether they had engaged in binge-drinking, without either providing a definition of "binge drinking" or asking participants to describe what they understand by the term (Elliott & Ainsworth, 2012; Woolfson & Maguire, 2010). This kind of assessment is flawed for two reasons:

1. Some participants might intentionally or subconsciously underreport their drinking behaviors for social desirability.
2. Different people might have a different understanding of what binge drinking is, which can significantly influence the responses of participants.

I decided to create my own measure for binge-drinking behavior consistent with the NIAAA's definition. In the second-wave survey, I asked all participants the same two questions:

1. How many days did you have four or more drinks on the same occasion?
2. How many days did you have five or more drinks on the same occasion?[3]

When I coded my data, a female binge drinker was identified by the four-drink criterion, and a male binge drinker was identified by the five-drink criterion.

Merging Datasets by Unique Identifier

As the whole study was a two-wave online survey, I needed to collect data twice among the same participants. This presented the challenge of how to *merge* the first-wave data and the second-wave data into a single dataset for analyses, making sure each participant in the first-wave survey corresponded to the same person in the second-wave survey. I could not ask participants to provide names or email addresses, because the surveys had to be anonymous to ensure confidentiality.

I asked participants' dates of birth and the first three letters of their mothers' first names. Then I combined these two string variables into a new variable named "unique_identifier." For example, if a participant was born on 01/01/1995, and the first three letters of his/her mothers' first name were Ana, then his or her unique identifier would be "Ana01/01/1995." While not impossible, the probability of any two participants having both the same date of birth and mothers whose names start with the same three letters is very low. After creating the unique_identifier variable in both surveys, I found (with the help of a Google search) an SPSS syntax that can merge two datasets together on a specific variable that appears in both of the datasets. After running the syntax, I obtained a merged dataset, which I then double-checked to make sure each person in the first wave was indeed matched to the same person in the second wave.

Data Cleaning

Data cleaning is a very important procedure before beginning analyses. If outliers are not removed from the dataset, they can significantly influence the results and produce faulty or biased findings. A good way to detect outliers is by plotting the histogram of each variable. For example, when I plotted the histogram of the age variable in the first-wave data, I noticed that there was a participant aged 120, which was basically impossible in a college-student sample (or any other, for that matter). It turned out that participant mistakenly filled out his year of birth as 1893, instead of 1993. In a case like this, a researcher needs to decide whether to make a manual correction or to delete it from the sample. As that participant's responses to other questions looked reasonable, I manually corrected 1893 to 1993 and retained this case. Also, as I used a 2-week time frame in my study, participants were asked how many days they had four/five or more drinks on the same occasion during the past *2 weeks* in the second survey. I considered any responses larger than 14 to be outliers, and I deleted those cases before proceeding with data analyses.

Data Analysis: Logistic Regression Versus Count Regression

When I conducted this study for my dissertation, I used hierarchical logistic regression to analyze the data as, at that time, I coded the binge-drinking behavior as a dichotomous variable: If a participant was a female, and if the number of days that she had *four or more* drinks on the same occasion (during the past 2 weeks) at Wave 2 was larger than 0, then this participant was coded as 1 = *binge-drinker*; if a participant was a male, and if the number of days that he had *five or more* drinks on the same occasion (during the past 2 weeks) at Wave 2 was larger than 0, then this participant was coded as 1 = *Binge-drinker*; all other cases were coded as 0 = *non-binge-drinker*. I thought hierarchical logistic regression was appropriate for analyzing my data.

This case study was submitted to *Journal of Drug of Education* (JoDE) in the spring of 2015. During the review process of this case for JoDE, one of the criticisms that I received from the reviewers was that the logistic regression used in this study was a suboptimal analytic strategy. The reviewers said that I should treat the outcome variable as a count variable and use count regression, rather than creating a binary outcome variable and using logistic regression. It had never occurred to me until that moment that my approach was suboptimal. I believed this criticism was valid, as dichotomization (i.e., creating a binary variable) results in a loss of the original richness of information, which subsequently leads to a decrease in variance accounted for in the outcome variable and a reduction in statistical power (Cohen, 1983, 1990). However, I was not familiar with count regressions, as that was the first time I had encountered a count outcome variable in my research.

I referred to the textbook *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd ed. (Cohen, Cohen, West, & Aiken, 2003) for my Advanced Statistics I class, which I took during the second year of my doctoral program. There I found that, when the outcome variable is a count variable, the residuals are not normally distributed; as such, ordinary least square regressions are inappropriate for analyzing count data. I did some further reading and found that count regression approaches (e.g., Poisson or negative binomial regression) are indeed much more appropriate for count data (Coxe, West, & Aiken, 2009). I finally decided to use negative binomial regression rather than Poisson regression, as the former accounts for overdispersion in count data (Cohen et al., 2003).

Redoing data analyses with a different statistical technique during the revise-and-resubmit process is often a pain in the neck. However, in a case like this, where the recommended technique is much stronger than the original, it is worth the time and effort, as it may reveal more accurate findings. I recoded the outcome variable as a count variable, followed step-by-step guidance for running negative binomial regression, and completed the analyses.

Comparing the results from the negative binomial regression with the ones from the original logistic regression, I noticed that the former appears to be a more powerful test than the latter. In the negative binomial regression, stress was a significant predictor, with a *p*-value of .001, whereas in the logistic regression, stress was still significant but with a *p*-value of .044. Although both tests found stress to be a significant predictor, the *p*-value in the negative binomial regression was much smaller than in the logistic regression.

Reflections on the Research Process: Practical Lessons Learned and Potential Strategies to Mitigate Weaknesses

In this section, I provide some reflections on the whole research process of our study[4] (Chen & Feeley, 2015). I discuss practical lessons I learned during the process, as well as potential strategies to mitigate its weaknesses in future research. Those strategies may be applicable for both survey research and experimental research.

Sample Profile

I collected data from a sample of undergraduates from one class (i.e., COM101). This made the sample not very diverse, and it might not represent the population of U.S. college students. COM101 is a lower level undergraduate class which is open to all students at the university. Students enrolled in that class include humanities and social science students, as well as natural sciences and engineering students. However, a majority of students were freshman. Ideally, it would be better to sample the whole university, with students from various departments and academic levels. This would make for a stronger study than using a sample of undergraduates from a single class.

Sample Size

A relatively small sample size can be a weakness for a study, but a sample size of 179 was probably sufficient for the data analysis purposes of our study. In their discussion on power and sample size, Carmen Wilson VanVoorhis and Betsy Morgan (2007) provided guidance on the selection of sample sizes, arguing that a minimum of 10 participants per predictor is appropriate for regression equations using six or more predictors. By this argument, our study would need a sample size of at least 100 participants (10 people per predictor × 10 predictors); our sample size is nearly double that.

In our study, 1 point of extra credit was provided to participants for filling out Wave 1 survey and 0.5 points for filling out Wave 2 survey. One possible strategy to recruit more participants is to increase incentives for participation, such as providing more points of extra credit, or adding monetary compensations (e.g., US$1-US$5) for each of the two surveys. Of course, the latter would be contingent on the funding available to researchers.

Attrition

The attrition rate of our study at Wave 2 is 35.8, which is a bit high. High attrition rate indicates that many participants in Wave 1 survey did not return to complete Wave 2 survey. Thus, I had been concerned that this might generate biased findings. In their study on attrition and generalizability in longitudinal studies, Kristin Gustavson, Tilmann von Soest, Evalill Karevold, and Espen Røysamb (2012) found that attrition rate in longitudinal studies did not influence estimates of associations between variables. They also concluded that “long-term longitudinal studies are valuable for studying associations between risk/protective factors and health outcomes even considering substantial attrition rates" (p. 1). Based on their findings, I am convinced that high attrition rate is not a serious problem for our study.

One way to reduce attrition may be to defer compensation for Wave 1 survey until participants fill out both surveys—that is, participants would get 1.5 points at the end of Wave 2 survey. Deferring compensation for Wave 1 survey may motivate Wave 1 participants to return for Wave 2 survey. Should monetary incentives be provided for the study, they should also be deferred to the end of Wave 2 survey.

Conclusion

Empirical researchers often face difficult choices when trying to decide on the most appropriate method to test hypotheses or answer research questions. A good study should be theory-driven, and researchers should always choose the most appropriate method and/or statistical technique that can serve the purpose of testing an existing theory or a proposed theoretical model, within time and budget constraints. Kurt Lewin's (1951) remark that "there is nothing so practical as a good theory" (p. 169) praises the value of theory in guiding many aspects of a research procedure, including research design and data analyses. However, a good study needs more than just a good theory. To make a good study, a sound and rigorous method is indispensable. A sound method will ensure that the design appropriately reflects the theoretical arguments, the sample reasonably represents the population, and the measured variables have good validity and reliability. Only after properly addressing these methodological issues, together with a careful choice of data analysis technique, can researchers ensure the accuracy and credibility of their findings.

The two-wave survey method presented in this case study is not perfect. Ideally, I would have designed a multiple-wave survey with repeated measures of predictors and the behavioral outcome. However, the two-wave survey is an improvement on the more frequently used cross-sectional design, which violates a basic theoretical assumption of the TPB—that the predicted behavior is a *future* behavior rather than a recalled *previous* behavior. Logistic regression, the original statistic technique used in this study, is not the best analytical strategy for a count outcome variable. I diligently complied with reviewers' request to conduct a count regression and obtained more accurate and credible results for this study. Some potential strategies (e.g., adding monetary incentives, deferring compensation) can be utilized to further improve its quality. In summary, I concur with Anthony Greenwald's (2012) counterpoint to Lewin: "There is nothing so theoretical as a good method" (p. 99).

Notes

1. During the blind-review process for *Journal of Drug of Education*, this was a comment from one of the reviewers.

2. This was another comment made by a reviewer for *Journal of Drug of Education*.

3. At the beginning of both surveys, participants were provided the following definition:

Throughout these questions, by a “drink” we mean a can or bottle of beer, a glass of wine or a wine cooler, a shot of liquor, or a mixed drink with liquor in it. We are not asking about times when you only had a sip or two from a drink. By “on the same occasion,” we mean within a 2-hour period.

Thus, when participants were filling out answers to questions including (a) “How many days did you have four or more drinks on the same occasion?” (b) “How many days did you have five or more drinks on the same occasion?”, they would know what “a drink” refers to and that “on the same occasion” means “within a 2-hour period.”

4. Thomas Hugh Feeley, my dissertation advisor, was added as the second author of this study when it was sent out for review, in recognition of his input. Thus, hereafter it becomes “our study,” rather than “my study.”

Exercises and Discussion Questions

1. What are the flaws of cross-sectional designs in research applying TBP? What is the advantage of using a two-wave survey design instead of a cross-sectional design for such study? What do you think is the weakness of a two-wave survey design compared with a longitudinal design?
2. Conduct a literature search on TPB studies focusing on binge-drinking behavior and published in the last 5 years (you can use “theory of planned behavior” and “binge-drinking” as key words in your search). Then create a Microsoft Excel spreadsheet listing measures of binge-drinking behavior in each of those studies. Compare all the measures (including the one from this study) and decide which one is the best. Explain your decision.
3. Explain reasons for merging first-wave survey with second-wave survey data. What other ways would you suggest for merging such data?
4. Is a high attrition rate a serious problem for a study using a prospective behavioral measure? Why or why not? What are some strategies you can offer to decrease the attrition rate?
5. The original TPB model does not include past behavior as a predictor of future behavior.

Conduct a literature search on TPB studies focusing on drinking, smoking, or other substance use, including past behavior and published in the last 5 years (you can use “theory of planned behavior,” “binge-drinking/smoking/substance use,” and “past behavior” as key words in your search). In each of the articles you find, read through the sections addressing “past behavior.” Did the authors provide justifications for why they included “past behavior” in the study? Do you agree with their justifications? Why or why not?

6. Regression analyses are often used to determine whether there is a relationship between a predictor and an outcome, as well as the strength of that relationship. Examples of regressions include linear regression, logistic regression, and count regression. Explain in what circumstance you would use each type of regression mentioned and why. This case study discussed two types of count regressions. Is one better than the other? Explain your answer.
7. Which aspect of the research procedure in this study do you think needs improvement? If you were about to conduct a study on binge drinking, what would you do differently (e.g., design, sampling, measures)?

Further Reading

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