The Impact of Interviewer Characteristics on Respondent Characteristics that Influence Item Non-Response
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Abstract
Missing information can impact analysis of data collected because replacement strategies impact the final analysis or cases with high item non-response (INR) are excluded from the analysis. There is not an abundance of empirical literature that investigates the impact of interviewer characteristics on respondent characteristics that influence INR. Survey research tends to focus on analyzing respondent characteristics or interviewer characteristics and their impact on INR. The current project investigates the impact of interviewer characteristics on respondent characteristics that influence INR in a statewide public policy survey.

Introduction
Large social surveys (i.e. General Social Survey, National Election Survey, Illinois State Policy Survey) are tools that academics and politicians use to understand what the population has to say about important issues. While some surveys are mailed or done with personal interviews, phone surveys are widely used because of random digit design, cost, and accessibility to a wide range of persons in the population of interest. The random digit design of phone surveys allows the equal probability for respondents because phone numbers are randomly generated. This allows for the inclusion of unlisted and unpublished phone numbers in the survey sample. Other methods (mail and interview) depend on location (i.e. address lists based on listed phone numbers or census tracts) or sampling strategy (i.e. voter registration or drivers license records), which can be problematic because some groups or people may be under represented or not even represented in the sample.

Item non-response (INR) some times attenuates the advantage that phone surveys provide of reaching a better probabilistic sample of the population. INR can be problematic for analyses of data and are often are handled with a variety of methods. Basically either a value is estimated by imputation or the entire case might be dropped from the analysis. Both methods of replacements have implications that can impact conclusions by influencing central tendencies or loosing information (Tabachnick & Fidell, 2000). Therefore, a deeper understanding of INR is important for survey data analysis and possibly even for design consideration.

The focus of this research is to investigate the contextual influences in phone surveys where the influence of interviewer characteristics on respondent characteristics might impact INR.

Phone Survey Effects on INR
Various cues impact respondents’ cooperation on survey items. The power of the situation is minimized in telephone surveys due to the lack of visual cues. For in-person interviews, respondents might use visual cues such as skin color or other ethnic identity cues to evaluate or make inferences about the interviewer. However, the lack of visual cues in a phone survey does not minimize the impact of audio cues and these audio cues may be obvious or subtle.

There are two cues that are considered to be obvious. The first is gender, which is often considered the easiest cue to recognize over the phone (99 to 95% accuracy rate). The second obvious cue, race, is reasonably predicted over the phone (Johnson, Fendrich, Shaligram, Garcy, & Gillespie, 2000; Wolford, Brown, Mardsen, Jackson, & Harrison, 1995). It has been found that 70% of respondents were able to correctly identify the race of the interviewer.

Subtle characteristics that are hypothesized to help the respondent identify race of interviewer are (a) interviewer name, (b) sound of voice, and (c) enunciation of words (Wolford, et al. 1995). These subtle cues might provide information so that it might be possible to draw inferences about such issues as educational level of the interviewer and/or respondent, the experience of the interviewer on a particular survey, and overall interviewer phone survey experience.

Interviewer Effects on INR.
Research findings on interviewer effects indicate that younger and less educated interviewers have a higher INR (Huddy, Billig, Bracciodieta, Hoeffer, Moynihan, & Pugliani, 1997). However the gender of the interviewer (O’Keefe, Boyd, & Brown, 1995) or previous interviewer experience (Singer, Frankel, & Glassman, 1983) do not have a significant impact on INR. An interesting finding on the report of 18-month drug use prevalence found that 31 to 40 year old interviewers elicited a lower INR and better cooperation than other 18 to 30 year old interviewers (Johnson et al., 2000).
Respondent Effects on INR

The other focus of research has been on respondent characteristics on the impact of INR. It has been found that INR increases with age (Ferber, 1966), negatively correlates with education (Ferber, 1966), females have a greater INR than males (Ferber, 1966), and whites have a greater INR than non-whites (Bell, 1984). It is interesting to note that according to this information older white poorly educated females should have the highest INR.

Further research regarding the interaction between interviewer and respondents found that older respondents were more susceptible to interviewer effects than younger respondents to interviewer effects (Groves & Magilary, 1986). However, in this study, interviewer effects were defined as the proportion of the between interviewer variance of the total interviewer variance. The results from the previous study do indicate an overall effect of interviewer but it lacks the investigation of the influence of specific interviewer characteristics on the impact of respondent characteristics.

INR Explained by the Interaction of Interviewer & Respondent Effects

While the current research does expand what is known about interviewer and respondent effects, it lacks describing the possible social cognitive influences. A possible social cognitive explanation for INR could come from the work on schemas and stereotyping. It is possible that during the survey process on the phone, the respondent might either automatically or intentionally stereotype the interviewer into a specific category by using schemas about audio information. Respondent cooperation on items within the survey (as operationalized as INR) may be dependent on whether the stereotype is a positive category (categorizing the interviewer into the respondent’s in-group) or a negative category (categorizing the interviewer into the respondent’s out-group).

Schemas could lead the interviewer or respondent to activate stereotypes about the other person in the interview. These stereotypes are difficult to suppress and they can function below conscious levels (Kunda, 1999; Moscowitz, Gollwitzer, Wasel, & Schall, 1999). While it is not necessarily good to use stereotypes, they are efficient. In the context of a phone interview that lasts 10 to 30 minutes where cognitive resources may be low, stereotypes function as energy saving devices in social cognition because they can simplify tasks and preserve processing resources (Macrae, Milne, & Bodenhausen, 1994). One other influence that might enhance the use of schemas and stereotypes is the fact that during an interview on the phone, both the interviewer and the respondent are not motivated to inhibit stereotypes.

Hypotheses

This research looks at interviewer effects as defined by interviewer race, age, gender, and education on respondent effects as defined by respondent race, age, gender, and education that impact INR. The first hypothesis includes respondent characteristics that influence INR consistent with previous research. The respondent characteristics of interest in this study are: (a) gender, (b) race, (c) age, and (d) education. Different from most of the other studies mentioned previously in this paper that investigate simple regression effects of respondent characteristics on INR, the current study will look at multiple respondent characteristics and their influence on INR.

$H_1$ There will be an impact of respondent gender, race, age, and education on INR.

In order to extend this research beyond previous research, the impact of interviewer characteristics will be examined as they influence respondent characteristics that impact INR. Respondents might be automatically stereotyping interviewers and these stereotypes consequently influence respondents’ decisions whether to respond or not to respond to items in the survey. Furthermore, it is expected that each interviewer characteristic of interest in this study will have a different influence on the respondent characteristics that impact INR in phone surveys.

$H_2$ Interviewer gender, race, and experience will differentially influence the impact of respondent characteristics of gender, race, age, and education on INR.

The last hypothesis states that the amount of experience an interviewer has on the survey tends to influence the average INR of the respondent.
characteristics. This would indicate that interviewers who spend more time working on a particular survey tend to elicit more cooperation from respondents independent of respondent characteristics that might elicit stereotyping.

$H_3$: Interviewer experience as operationalized by number of completed cases in this survey will have a significant impact on the intercept for respondent characteristics that influence INR.

**Methods**

The data used for the current survey come from the Illinois Policy Telephone Survey conducted for the Center for Governmental Studies by the Public Opinion Laboratory at Northern Illinois University. This was a RDD survey conducted during the fall of 2000 with 1206 respondents. This survey has been conducted annually since 1984. A disproportionate sample was used in order to achieve approximately equal number of respondents for 6 geographical areas of Illinois.

Topics in the survey asked residents’ opinions about the most important state problem, priorities for state spending, the quality of life in Illinois, education issues, and evaluations of public officials. The outcome rates for the survey were computed using the 2000 APPOR standards. Since partial interviews were not used in the analysis, response rates were determined for the minimum response rate ($RR1 = 23.75\%$) and the fifth response rate where none of the cases of unknown eligibility are considered eligible ($RR5 = 27.6\%$). The cooperation rate was $74.4\%$ ($COOP1$), which is the minimum cooperation rate computation. Refusal rates were computed for all 3 computations from the minimum refusal rate ($RR1 = 8.15\%$), the second refusal rate that includes an estimate of the proportion of unknowns that were actually eligible ($RR2 = 8.64\%$), and the maximum refusal rate ($RR3 = 9.48\%$). The contact rates were also computed for all three formulas ($CON1 = 31.9\%$, $CON2 = 33.7\%$, and $CON3 = 37\%$).

There were 55\% female and 45\% male respondents with a mean age 46 (SD=16). Eighty three percent of respondents indicated they were white and the remainder (17\%) was classified as other. Of this other racial group, less than 2\% of respondents were non-black with 98\% of this other racial group indicating they were black. For education of respondents there was a bi-modal distribution with peaks at ‘high school diploma’ and a second peak at ‘2 years of college and some college.’

Interviewers of the Public Opinion Laboratory received informed consent and volunteered demographic information that is kept in confidential files and not accessible by persons in the organization who have decision authority over them. There were 62 Public Opinion Laboratory interviewers working on this particular survey. There were 63\% female interviewers and 37\% male interviewers. For race, 63\% of interviewers were white and 37\% were classified as other. The other racial category for interviewers, similar to the other race category for respondents contains less than 2\% non-black. Experience was operationalized as the number of State Poll surveys completed by the interviewer with a mean of 19.45 (SD=15.4). The mean age of interviewers was 23 (SD=7.56).

For all analyses, the INR will be computed as a percentage where the numerator is the number of items for non-response divided by the number of items in the survey asked of each participant. There is minimal branching in the survey so that possible difference of topics asked about and number of items asked of each respondent would not impact the results.

**Results**

Regression technique for identifying outliers was performed on the survey data for the interviewer characteristics and the INR (Tabachnick & Fidell, 2000). Mahalanobis distance was calculated and those respondents whose distance was greater than 20.515 were not included for any analyses. When outliers were removed from the data set, 1181 respondents were used for all analyses.

The first hypothesis was not fully supported as that respondent characteristics except race were significant predictors when INR was regressed on the respondent demographics. When considering just the respondent characteristics, INR percentage is significantly predicted by the intercept, respondent age, gender, and education (Table 1).

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>SE B</th>
<th>ß</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>6.672*</td>
<td>.421</td>
<td>.082</td>
</tr>
<tr>
<td>Age</td>
<td>0.0017*</td>
<td>.006</td>
<td>.082</td>
</tr>
<tr>
<td>Education</td>
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<td>-.069</td>
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<tr>
<td>Gender</td>
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<td>-.076</td>
</tr>
<tr>
<td>Race</td>
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<td>.258</td>
<td>-.044</td>
</tr>
</tbody>
</table>

Note. $R^2 = .145$; *p<.05

The second and third hypotheses were tested using hierarchical linear modeling. An unconditional model was specified first and indicated that there was an impact of interviewer on the respondent that influences INR ($p<.001$). A specified model that
tested the hypothesized effects of interviewer gender, race, and experience differentially influencing the impact of respondent characteristics of gender, race, age, and education on INR was then conducted.

Significant findings of the specified model include: (a) interviewer age (p<.027) impacted the overall respondent influence on INR, (b) interviewer race (p<.027) and age (p<.021) impacted the influence of respondent age on INR (c) interviewer age (p<.017) impacted the influence of respondent education on INR.

Interviwer experience as defined as the number of completed cases did not significantly impact the general respondent influence on INR. However, there was a significant impact of interviewer experience (p<.025) on the influence of respondent race on INR.

Conclusions

There is an impact of interviewer characteristics on respondent characteristics that influence INR. Age of interviewer is a more important factor than gender or race of interviewer on general opinion surveys. Interviewer experience on a survey might help minimize the impact of respondent race on INR. Investigation of INR on phone surveys needs to contain information on both the respondent and the interviewer.

While this information does not apply to all question or survey types, it does indicate that when evaluating the INR in a survey, the impact that the interviewer has on respondent characteristics should be taken into consideration. To indicate INR is just an effect of respondent or interviewer characteristics would leave out an important aspect of INR.

Future Directions

Further investigation of ability to determine race on phone interviews should be conducted. At this point in time, there have been only limited studies on this important issue. Further work on this topic might clarify present results. In addition, the type of questions asked should be investigated for whether they are personally threatening, such as sexual behavior, illegal drug use or non-threatening such as attitudes about state policy.

References


