Who do phone surveys miss, and how to reduce exclusion: recommendations from phone surveys in nine Indian states

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INTRODUCTION

Household surveys are a useful tool to understand the socioeconomic conditions prevailing at a given time, which can help design better policies for the future. Given the demanding nature of face-to-face data collection and the rise in mobile phone ownership in low-and-middle-income countries (LMICs) over the last few years, researchers have begun using mobile phone surveys (MPS) to collect household survey data. Such surveys offer the promise of collecting timely, high-quality data at low cost.¹² These errors can arise due to differences between those who own and those who do not own mobile phones (non-coverage error),¹⁰ ¹¹ as well as differences between those who respond and those who do not respond to surveys (non-response error).¹² Therefore, when implementing CATI–MPS, practitioners should pay close attention to these incentives have no statistically detectable effect on households in other income groups.

ABSTRACT

Computer-assisted telephone interviews (CATI) through mobile phones are a low-cost, rapid and safe way to collect data. However, decisions for how such mobile phone surveys are designed and implemented, and their data analysed, can have implications for the sample reached, and in turn affect the generalisability of sample estimates. In this practice paper, we propose a framework for extending the use of CATI–mobile phone surveys in India, which can be applied broadly to future surveys conducted using this method. Across the stages of design, implementation and analysis, we outline challenges in ensuring that the data collected through such surveys are representative and provide recommendations for reducing non-coverage and non-response errors, thereby enabling practitioners in India to use CATI–mobile phone surveys to estimate population statistics with lower bias. We support our analysis by drawing on primary data that we collected in five mobile phone surveys across nine Indian states in 2020. Our recommendations can help practitioners in India improve the representativeness of data collected through mobile phone surveys and generate more accurate estimates.

Summary box

- Computer-assisted telephone interviews–mobile phone surveys are susceptible to bias arising from non-coverage and non-response errors. Drawing on original data collected as part of five phone surveys across nine Indian states, we find that non-coverage and non-response errors are correlated with household income and other relevant characteristics.
- To reduce non-coverage errors, we recommend that practitioners adjust their sample estimates using poststratification weights and also discuss the limitations of this approach.
- To reduce non-response errors, we recommend that practitioners follow structured callback protocols and call households at the optimal time of the day for the given context. We found these strategies to be effective across all income groups.
- To account for non-response errors arising from households refusing to participate in the survey, we find that offering airtime incentives can improve the likelihood that households in the bottom income quintile consent to surveys, but these incentives have no statistically detectable effect on households in other income groups.
minimise non-coverage and non-response errors. Doing so requires empirical evidence on the extent of these errors. While such evidence is growing for LMICs, to our knowledge, it is still very limited for India.\(^5\)\(^13\) In this paper, we propose a framework to explain the sources of bias due to non-observation errors at different stages of an MPS, design, implementation and analysis (figure 1), and recommend ways to reduce the resulting bias. To support our recommendations, we draw on primary data that we collected across five different phone surveys in nine states across India in 2020 (online supplemental box).

At the design stage, we recommend that practitioners document coverage bias by analysing the correlation between mobile phone ownership and socioeconomic and demographical characteristics.\(^14\)\(^15\) We also highlight different characteristics of sampling frames that can be used to assess their effective coverage to reduce non-coverage errors. At the implementation stage, we recommend protocols and interventions to decrease two important sources of non-response errors: (1) respondents who own mobile phones may not answer them, and (2) respondents who answer their mobile phone may not consent to participating in the survey. At the analysis stage, practitioners have a more limited toolkit and can construct poststratification weigths and/or account for mode effects.\(^16\) We do not discuss these methods in this paper given their sufficient treatment elsewhere.\(^17\) Our recommendations add to the limited body of work on CATI and MPS in the Indian context and will help practitioners to improve the quality of data collected through MPS in the future.

**DESIGN STAGE**

At the design stage, practitioners must decide how to construct a sampling frame of mobile phone numbers from which they can sample households. These sampling frames can be constructed from a variety of sources: through face-to-face surveys in which enumerators collect mobile numbers, through household lists maintained by the government or private companies or through random digit dialling. The sampling frames we draw on in this paper were obtained from face-to-face surveys conducted the previous year by our organisation, in which we asked households whether they possessed a mobile phone, who the primary owner was, and what the number was.

We argue that practitioners should pay attention to two features of sampling frames at the design stage: (1) what percentage of the target population is covered by the frame and how that coverage correlates with demographical and socioeconomic characteristics (‘coverage’) and (2) what percentage of mobile phone numbers are answered by the correct household (‘yield rate’).
In our sample, we find that both sources of non-response error are correlated with household income levels. Households belonging to the top income quartile are 7.7 percentage points more likely to answer the phone (evaluated using a two-sided t-test: p<0.01 and n=10 170; table 2) and 5.6 percentage points more likely to consent to the survey (evaluated using a two-sided t-test: p<0.01 and n=10 170; table 2), as compared with households belonging to the bottom three income quartiles. Given this difference, it is important that researchers implement protocols that improve response rates, especially among lower income households.

To address concerns related to respondents not answering their phone, we recommend that practitioners use structured callback protocols and identify the best time of the day to call the respondents. To address concerns related to respondents not consenting for the survey, practitioners could consider using incentives, ensure the survey length does not exceed 30 minutes, and ensure that the enumerators’ script is conversational and engaging. Below, we discuss how callback protocols, identifying the optimal time of the day to call, and incentives can address non-response bias. We do not discuss face-to-face baseline survey, or by obtaining neighbours’ phone numbers to contact the intended household.

**Table 1** Mobile phone ownership rates by income quartile*

| Income quartile | Mobile phone ownership rate | N   |
|-----------------|----------------------------|-----|
| Top 25%         | 93.8%                      | 5249|
| 50%–75%        | 83.9%                      | 5795|
| 25%–50%        | 85.1%                      | 6647|
| Bottom 25%     | 85.0%                      | 7168|
| Top 25%        | 93.8%                      | 5249|
| Bottom 75%     | 84.7%                      | 19 610|

*Income quartile represents the range in which a household’s monthly income falls. Since our sampling frame data only included an income range as opposed to a continuous value, the number of households in each quartile is not equivalent. The bottom 25% quartile represents households whose monthly income was between 0 and 2999 Indian Rupees (INR), the middle 25%–50% quartile represents a monthly income of 3000–4999 INR, the 50%–75% quartile represents a monthly income of 5000–8999 INR, and the top 25% quartile represents a monthly income of over 9000 INR.
survey length and introductory scripts given their sufficient treatment elsewhere.

**How many times should you try to call a household?**

Enumerators may experience challenges reaching respondents during a CATI–MPS: respondents may not answer the mobile phone, the mobile phone may be out of battery charge or airtime or outside the network coverage area. These challenges can produce biased survey estimates when they are correlated with household characteristics. In order to mitigate these challenges, enumerators will typically need to make multiple attempts to call the household before being able to speak to a member of the intended household.

We find that designing a structured callback protocol in which we specify the times during the day to call the household, and the number of attempts to make, increases the probability of reaching the intended household. In a pilot phone survey in Jharkhand, we attempted to reach 200 households without following a structured protocol. We instructed enumerators to try as best as they could to reach the intended household, but did not provide any additional guidance such as the time of the day to call them or the number of attempts to make in case previous attempts were unsuccessful. Our response rate, defined as the proportion of respondents who completed the survey, was 30%.

In a subsequent survey, we instituted structured callback protocols. We designed two protocols and sampled 100 households per protocol from the same sampling frame as the previous two pilots (Rural Districts (RD) frame, online supplemental box). In the first protocol, we randomised when during the day (morning, afternoon or evening) enumerators called the households. If the household was not reached, it was called back in the subsequent time slot (eg, if the household was initially called in the morning and did not answer, they were called back in the afternoon), up to seven times. In the second protocol, after a failed attempt, households were only called in the morning or evenings, with follow-ups placed after the hour in each slot. The response rate was 70% for the first protocol and 55% for the second protocol (the difference between the two protocols is statistically significant using a two-sided t-test: \( p=0.046 \) and \( n=200 \)), with both protocols yielding higher response rates than our pilot phone surveys that lacked structured protocols. This experiment suggests that using a structured callback protocol can help practitioners improve the response rate from CATI–MPS.

With our seven attempts protocol described in figure 2, we find that there are diminishing returns from additional attempts to reach the household. When disaggregating by income quartiles (figure 3), we observe that (1) the response rates are higher for the richest households across all seven attempts (9.2 percentage points higher for households in the top income quartile); and (2), while additional callback attempts improve the survey response rate for all income quartiles, the relative ordering of income quartiles remains the same. Therefore, we conclude that using the seven attempts protocol described in figure 2 can help improve the likelihood of reaching households across all income quartiles.

**Table 2**

| Income quartile | Phone answering rate | Completion rate | N  |
|-----------------|----------------------|----------------|----|
| Top 25%         | 67.5%                | 59.3%          | 2501|
| 50%–75%         | 63.3%                | 56.7%          | 2180|
| 25%–50%         | 62.1%                | 50.1%          | 2274|
| Bottom 25%      | 55.8%                | 49.9%          | 3215|
| Top 25%         | 67.5%                | 59.3%          | 2501|
| Bottom 75%      | 59.8%                | 53.6%          | 7669|

**Figure 2** Callback protocols for computer-assisted telephone interviews–mobile phone surveys.
When during the day should you call a household?

In our surveys, we randomly assigned the time of the day when enumerators would call households for the initial call attempt. This meant that there is a roughly uniform distribution of attempts made across different times of the day. For our COVID-19 Knowledge, Attitude, and Practice (KAP) surveys, we observe that respondents were more likely to complete surveys during the morning slots. Roughly 27% of our households were reached between 9:00 and 11:00. We find that only 17.8% of households were available to be surveyed in the evenings after 17:00, likely because household members were engaged in preparing and eating dinner. Figure 4 shows the distribution of completed surveys based on the household’s income quartile and the time of the day when the household was called. The patterns are similar across income quartiles. Therefore, we conclude that the optimal time of the day to call households does not vary based on the income levels of the sampled households. However, we acknowledge that other contextual factors may affect response rates, such as seasonal variation based on the agricultural cycle. We recommend that practitioners collect data on response rates by time of the day and adjust callback protocols accordingly to improve response rates.

Figure 3 The cumulative proportion of completed surveys by attempts and income groups.

Figure 4 The proportion of completed surveys by time of the day and income groups.
Does offering incentives increase consent rates?

As outlined in figure 1, after overcoming challenges of reaching the intended households using appropriate protocols, the next step is to encourage respondents to consent to the survey. Increasing consent rates can reduce the bias arising from differences between households where a member consents or refuses to proceed with the survey after answering the call from the enumerators.

In an attempt to maximise consent rates, some researchers have hypothesised that offering incentives can increase the likelihood that respondents consent to MPS, and some studies have found that monetary incentives can be effective. However, since there is no physical contact between the enumerator and the respondent in CATI–MPS, there are limited options for the types of incentives that researchers can provide. One promising incentive that can be easily delivered is an airtime top-up for mobile phone users. The evidence on the effect of airtime incentives on consent rates for CATI–MPS is inconclusive. In our COVID-19 household surveys, we tested whether airtime incentives improved the survey completion rates among households where a member answered the phone. To do this, we conducted a two-arm individual-level randomised experiment to measure the effect of providing airtime incentives on survey completion rates for two rounds of our COVID-19 econ survey with the rural population sample (online supplemental box). In group 1, prior to seeking consent, we informed respondents that if they completed the current and a subsequent survey round, they would receive 100 INR (US$1.37) as a mobile airtime top-up after both survey rounds were completed. In group 2, we did not mention any incentives.

We find that the difference between completion rates, defined as the number of completed surveys of the households who answered the phone, is not statistically significant between the two groups (evaluated using a two-sided t-test: p=0.1864 and n=1370). This could be the case because most households in our sample may not value airtime incentives, particularly since Indian mobile companies offer very low rates for mobile telephony. However, when we compare the completion rates between respondents in the two treatment groups by income quartile, we observe that incentives do affect response rates for households belonging to the lowest income quartile. As shown in figure 5, for households belonging to the bottom income quartile, offering airtime incentives increased their survey completion rate by 9.8 percentage points (evaluated using a two-sided t-test: p=0.069 and n=243). The differences in completion rates across the other income quartiles are not statistically significant. This suggests that practitioners can potentially use airtime incentives to increase response rates with lower-income households. Future research is needed to examine the effectiveness of other types of incentives, such as direct cash transfers.

CONCLUSION

During the COVID-19 pandemic, the use of CATI–MPS has grown substantially in India. However, these surveys

Figure 5 The proportion of completed surveys by incentive group and income group.
remain prone to significant non-coverage and non-response errors, which could bias the resulting sample estimates. In this paper, we draw on original data from five phone surveys across nine Indian states to offer practitioners several recommendations for reducing bias at different stages of a CATI–MPS. At the design stage, we recommend that practitioners consider two features of sampling frames to minimise the non-coverage error: their coverage (proportion of households where at least one member possesses a mobile phone) and the yield rate (percentage of mobile numbers in the sample that are answered by the correct household). If the coverage of the sampling frame is correlated with relevant household characteristics, practitioners can use poststratification weights, but this strategy is an imperfect solution. At the implementation stage, we recommend various steps to reduce non-response rates. First, using a structured callback protocol can improve response rates across households of all income quartiles. Second, calling at different times of the day can help practitioners reach households of all income groups, with morning slots yielding higher response rates across all groups. Third, providing airtime incentives in return for completing the survey improves the response rates among the poorest households. These findings and recommendations can help practitioners reduce bias at each stage of the survey and generate more accurate sample estimates from CATI–MPS.

Acknowledgements We thank the Bill and Melinda Gates Foundation for their financial support for this study.

Contributors AB contributed to designing the experiments, research questions and report writing. MRM contributed to designing research questions, data cleaning, data analysis, data visualisations and report writing. KN contributed to designing research questions, data analysis, editing and report writing. AF provided guidance on research questions and contributed to report writing.

Funding This research is funded by the Bill and Melinda Gates Foundation.

Competing interests None declared.

Patient consent for publication Not required.

Ethics approval Ethics approval was obtained from IDinsight’s internal ethics review committee for data collected and used for analysis in this paper. Only those participants who provided verbal consent were interviewed.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon request.

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