
Reaching Hard-To-Reach Populations: an Analysis of Survey Recruitment Methods

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ABSTRACT

This work examined the survey distribution methods used in a past study. The goal was to identify the most effective methods to reach marginalized voices to participate in technological research and thus, create more inclusive technologies. Initial analyses identified in-person onsite recruitment as one of the better methods for reaching hard-to-reach populations compared to M-Turk, social media, newsletters, mail, and text messages. Our results call for continued efforts to use more inclusive research methods in the field of HCI.

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CSCW '19 Companion, November 9–13, 2019, Austin, TX, USA

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ACM ISBN 978-1-4503-6692-2/19/11.

<https://doi.org/10.1145/3311957.3359447>

ACM Reference Format:

Xuecong Xu, Xiang Yan, and Tawanna R. Dillahunt. 2019. Reaching Hard-To-Reach Populations: an Analysis of Survey Recruitment Methods. In *2019 Computer Supported Cooperative Work and Social Computing Companion Publication (CSCW '19 Companion)*, November 9–13, 2019, Austin, TX, USA. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3311957.3359447>

INTRODUCTION

When technological innovations are introduced to the public realm with promises of improving human well-being, disadvantaged populations are often left behind in the conversation [4]. Therefore, technological advances sometimes end up not lifting the life experiences of those who are disadvantaged and can lead to further disadvantages. Reports on predictive inequality in artificial intelligence (AI), for instance, are on the rise [2, 5, 9]. To create more inclusive technologies, both industry developers and academic researchers should aim to incorporate the voices of those who have seldom been heard and who are often "hard-to-reach".

"Hard-to-reach" or "hidden" populations are defined as the socially disadvantaged groups who face barriers with transportation, digital literacy, and financial access, which make it difficult for researchers to reach them in cost-efficient ways [11]. HCI researchers have recognized the importance of inclusive research and design [3, 4], and have identified a few effective strategies for recruiting hard-to-reach populations such as snowball sampling [1], respondent-driven sampling [6], and leveraging community networks [7]. Leveraging community networks to recruit face-to-face is one of the most effective ways of reaching them, while anonymous web-based surveys have become more frequently adapted to *overcome* the limitation of in-person recruitment [8]. Recognizing the importance of continuing the discussion about conducting research with disadvantaged populations, especially in technology-based research [8, 10], we analyzed the distributional methods of a web-based Qualtrics survey and contribute insights into ways to conduct technology-based research among hard-to-reach communities.

METHODS

In a separate study to gauge traveler's preferences on future Mobility-On-Demand (MOD) transportation services, researchers conducted a web-based Qualtrics survey, and distributed the survey link through a variety of means including using postal mailings, sending text messages, posting on online social media platforms including Facebook and Nextdoor, posting on community newsletters, recruiting through Amazon Mechanical Turk, and having research assistants sharing the survey link to potential participants in-person at public libraries and non-profit organizations [12]. Researchers distributed the surveys in two low-resourced geographies in southeastern, Michigan, in an effort to reach hard-to-reach and low-income groups.

Amazon M-Turk	\$146 for posting on the platform
Internet Social Media	No additional cost.
Postal Mailing	\$172.19 for printing and reproduction; \$525 postage.
Community Newsletter	No additional cost.
Text Messages	\$300 for phone list purchase; \$70 for Twilio messages.
In-person	Research assistants' hourly wage of \$15-\$18.

Figure 1: Additional cost. (http://deepblue.lib.umich.edu/data/concern/data_sets/zs25x8453).

Method	Avg. income
In-person	\$19,690.16
Text Messages	\$32,012.04
Amazon M-turk	\$56,240.24
Community Newsletter	\$77,940.77
Postal Mailing	\$89,705.41
Online Social Media	\$83,823.09

Figure 2: Average income of participants in each recruitment group.

This study focuses on all five methods employed to distribute the survey link to assess the effectiveness of the survey distributional methods employed in terms of their response rate, cost-effectiveness, and ability to reach the targeted population. We recorded several important data-sets for each method: number of people contacted, number of complete responses, number of valid responses that passed a screening process, and total cost, as shown in *Figure 1*. These numbers were used to calculate response rate and cost per valid response. In addition, we took participants' self-reported household income in the survey as an indication of their socioeconomic status.

Response Rate. As shown in *Figure 1*, we divided the number of complete response by the number of people contacted for a *crude response rate*. Because of the difficulty of knowing the exact number of people contacted, we also calculated a *valid response rate*, or % of valid response received, by dividing the number of valid response that passed a screening process by the number of complete response.

Cost-Effectiveness. In addition to compensation for each complete response, each distributional method was associated with additional cost listed in *Figure 2*. The cost effectiveness for each method was calculated by dividing the total cost by the number of valid response.

Ability to Reach Target Population. Based on the self-reported household income in the survey, we cross-tabulated participants' income with the distributional method through which they were contacted. We then calculated the average household income in each group.

PRELIMINARY RESULTS

In terms of response rate, we could not calculate the crude response rate because of lack of access to the exact number of people contacted in all cases except postal mailing (5.4%) and text messages (0.3%). We did, however, find that text messages (100%), postal mailing (97.53%), Amazon Mechanical Turk (96.32%), and in-person (81.73%) received the highest percentages of valid responses.

The majority of methods cost approximately \$10-\$20 dollars per valid response, while text messages (\$35.83 /valid response) cost significantly more and Amazon Mechanical Turk (\$3.65/valid response) cost significantly less than others. It is important to note that, distributing the survey link through text messages is in fact very inexpensive. The high cost we found here was due to an extremely low crude response rate—we only received 12 responses out of 4000 messages sent. Also, text messages may often be perceived as intrusive, making the online survey link untrustworthy to follow.

Our ability to reach the targeted hard-to-reach population was measured by survey respondents' household income. Based on the average household income of participants by recruitment method, we found that recruiting through in-person (\$19,690.16) and text messages (\$32,012.04) helped us reach our target populations most effectively.

Method	Number of People Contacted	Number of Complete Response	Crude Response Rate	Number of Valid Response	Total Cost	Valid Response Rate	Cost per Valid Response
Amazon M-Turk	n/a	136	n/a	131	\$478.00	96.32%	\$3.65
Community Newsletter	n/a	281	n/a	123	\$1,405.00	43.77%	\$11.42
Internet Social Media (Facebook/Nextdoor)	n/a	903	n/a	395	\$4,515.00	43.74%	\$11.43
Postal Mailing	1500	81	5.40%	79	\$1,102.19	97.53%	\$13.95
In-person	n/a	208	n/a	170	\$3,370.90	81.73%	\$19.83
Text Messages	4000	12	0.30%	12	\$430.00	100.00%	\$35.83

Figure 3: Preliminary results.

DISCUSSION

Compared to other methods, in-person onsite recruitment at public libraries and non-profit organizations was the most effective in reaching our targeted populations based on participants' household income. Although this method can be somewhat costly and time-consuming, it allowed the research team to directly identify people who were uncomfortable using or who lacked access to digital devices. On the other hand, technology-enabled methods such as advertising through online platforms, text messages, and Amazon Mechanical Turk required a certain level of digital literacy and access, thus excluding population segments with technological barriers.

More direct research methods such as community-based and participatory (CBPR) methods serve to make research methods more inclusive [4]. While in-person and CBPR methods alike may require more time and financial resources than surveys, sample sizes matter more for surveys. Therefore, we encourage scholars to view these research methods as complementary to each other and continue to find ways to best utilize them both.

CONCLUSION AND FUTURE WORK

In this analyses of survey distribution methods, we identified the in-person onsite method to be the most effective in reaching hard-to-reach populations, while having moderate cost and relatively high response rates. Reaching those with limited access to technology requires that we break away from our traditional and often "convenient" research methods to reach them.

ACKNOWLEDGEMENTS

This work was supported by the University of Michigan's Poverty Solutions. We thank our participants and the Social Innovations Group for providing helpful comments on this work.

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