Data Collection Methods to Improve Measurement of Community Contextual Features

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Abstract

Data on community context is an increasingly important part of social, behavioral, and medical studies. These data are designed to capture aspects of a respondent's surrounding at a level of measurement above the single individual. There are several challenges, however, that impede the collection of accurate community context data in both developed and developing settings. We present the results of a pilot test in Chitwan, Nepal, that uses an improved instrument containing two key innovations: (1) a respondent-focused interface design featuring touch input and large map displays and (2) efficient field-based GIS. These two features are designed to promote respondent-interviewer collaboration. The results suggest that the instrument is highly usable by a wide range of respondents, even those who have never used a computer before. Usability appeared to be lower among less educated and older respondents, but this did not detract from the overall success of the instrument.

Introduction

Data on community context is an increasingly important part of social, behavioral, and medical studies. Sometimes called neighborhood context, contextual data, or social context, these data are designed to measure aspects of a respondent's surrounding at a level of measurement above the single individual. Adopting multilevel statistical methods, researchers are able to take advantage of ever more detailed spatial and individual level information to achieve a comprehensive picture of how communities may be associated with health, education and socio-economic mobility across diverse settings (Crowder & South, 2011; Sastry & Pebley, 2010). It is clear that community context instruments (CCI) are important tools that have significant use in contemporary research.

Despite these successes, there are several issues that decrease the usefulness of the CCI in surveys and present a distinct challenge to improved contextual data collection in developing settings. First, precise spatial measures of community context are challenging to collect particularly in settings where comprehensive number address systems are not used. In developing countries, places are often identified simply by village, neighborhood, or district name. Thus the location of important community features, such as schools, places of employment, or health care facilities are collected with relatively low precision. Similar challenges emerge in rural and remote areas of developed countries resulting in poorer quality data for some groups, such as Native Americans, than others (Wey et al. 2009). Contextual data in these settings are often reduced to a dichotomy (does the village have the feature or not) or a general radial measure of distance (how far away is the nearest feature). Not specifying a precise geographic location creates additional measurement error because respondents must not only cognitively recall the feature in question, but they must also estimate physical distance or travel time to the recalled feature: a task that has high error (Horning, El-Geneidy, and Krizek 2008). The potential errors in these tasks are further compounded when respondents are asked to recall retrospective contextual data.

Second, because of the cognitive difficulty and time it takes to recall contextual features in settings that do not use numeric address systems, researchers often use a group of informants with CCI to increase recall and breadth of information. While this approach may result in reasonably comprehensive data, the resulting community measures may not actually reflect the exposure of any one individual to various contextual features: e.g., the informants may precisely locate the school nearest the community, but it remains unknown which community members actually use that specific school. This potentially creates mismatch when community-level data is merged with data from individual respondents.

The third challenge for CCIs in developing settings, as currently constructed, is that they have not taken full advantage of the visual cues or maps that are likely to increase respondent spatial recall. Maps are one of the most important visual aids for cuing the recall of spatial memory, but using maps in the field in developing settings is challenging. To identify features such as individual buildings, roads, and landmarks on satellite imagery, a very high level of resolution is needed: less than 2 meter/pixel resolution. It is not feasible to bring a complete set—at multiple zoom levels—of printed maps to an interview, page through them, and record a location identified by respondents.

Our research directly addresses these three challenges to collecting comprehensive and individually-relevant community context data in developing or rural settings where comprehensive number address systems are not used. In this paper, we explain the development of an innovative computer assisted interview (CAI) community context instrument (CCI). We also provide pilot data from a small field test from Chitwan, Nepal, that demonstrates its feasibility.

Background

Dimensions of community have been linked to many outcomes including family behaviors, educational attainment, and economic mobility. Community context has been conceptualized in different ways: measures of the social context of the community as well as physical features of the community. For example, studies have linked community collective efficacy, trust, and fear to important outcomes. In these studies, community social context is a report of social perceptions, sometimes from individuals but other times from groups of individuals in a community that are then aggregated. In contrast to social perceptions, other measures of community context include reports of an individual's physical surrounding, such as the location or accessibility of schools, roads, health clinics, grocery stores, or churches. Community context measures are important because many hypotheses predict that individual actions are constrained or facilitated by these community-level factors.

Limitations have impeded the collection of accurate measures of physical community context. These problems arise both in settings that use numeric address systems and those that do not. For example, the LAFANS project in Los Angeles is a leading study for examining links between neighborhoods and health, socioeconomics, and family well-being. LAFANS asked respondents for precise location data (numeric addresses or cross-streets) on the physical location of places respondents frequented, such as grocery stores, churches, and prior residences. Even though detailed location data were requested of places just within Southern California, only about three-fourths of locations were successfully geocoded (Pebley and Sastry 2004).

Collection of detailed location data is even more limited in areas that do not use numeric address systems, such as developing settings. Because the locations cannot be referenced by an address that can be written down and later geocoded, more limited spatial data is usually collected. Data collections often ask if there is or is not a certain type of organization or infrastructure in the area, such as a school, hospital, or road. While this approach may be acceptable for very rural areas that have few of these features, this approach limits the accuracy of community context data. In urban or peri-urban areas that are experiencing rapid development of organizations, simply knowing if there is or is not an organization in the community is insufficient: individuals may use transportation infrastructure, or other means of travel such as bicycles, to go outside the community. Alternatively, some data collections ask how far away the nearest organization is, but this also has limitations. In rapidly developing settings there is often a choice of organizations: schools, markets, health clinics. There is heterogeneity in these organizations: some are public, some are private; some are free, others require payment; some promote wide participation, others are exclusionary. Knowing only the distance to the nearest organization provides a limited measurement of context because it is unknown if the respondent actually participates in it. Another strategy sometimes employed to collect community context information in these settings is to rely on group interviews. But in this case, the data do not inform us about who participates in a specified organization. Data collections often use group interviews because it is a burdensome task to request detailed location data from a single individual in a settings that does not use numeric address systems. Group interview of community context data allows the individual-level interviews to be shorter length; the community context data can later be appended and merged to all individuals living in that community. The drawback is that the community context data may not accurately reflect any one specific individual’s experiences.

Another limitation to collecting highly precise contextual data is the inability to easily use maps in the data collection process. Given the strong connection between imagery and the memory recall (Knez, 2006; Rubin, 1996), the rate and quality of recall could be significantly enhanced by implementing spatial cueing opportunities. Because physical locations are intrinsically tied to memory (Conway & Pleydell-Pearce, 2000), an instrument that uses maps could be a valuable resource. This will increase both the likelihood that features are recalled, as well as the resolution of the features already remembered. Unfortunately, most currently used community context instruments do not provide the opportunity to present any such spatial cues, even as simple as a map. While interviewers could carry a few supplemental maps, most activities are not confined to a limited area so it is easy to imagine that there would be several cases where the available maps or materials would not be sufficient for a given individual. Furthermore, going through multiple pages of maps or finding space for a large map is awkward in a field survey and can consume valuable interview time. Most prior research on maps in field surveys has focused on field staff using maps to find respondents (Nusser, 2007), not map use during interviews. Sinibaldi et al. (2006) explored using digital maps to interview respondents, but they measured a single domain (location of alcohol consumption) and did not use a mobile, field-based instrument.

Although highly precise community context data is usually not collected in most developing settings, there are several reasons why this precise data is needed. First, previous studies have reported strong associations between community context and individual outcomes, while others have found weak or no influence of community context, even when these associations have been strongly predicted by theory. Imprecise measurement may be a contributor to these unexpected findings. The community context may not have been reported accurately by respondents or informants, or the context reported by a group of informants many not represent the context as experienced by other individuals in the dataset. The latter possibility is particularly problematic: while misreporting the distance to a local school by 400 meters, for example, is likely to introduce merely random measurement error, there could be severe biases if the school reported by a group of informants is not accessible to a respondent whose is matched to that community context measure. Perhaps the respondent is not wealthy enough for his or her children to use the school, or the school is open only to members of a certain ethnic group.

The second reason why precise community context data is needed is because new spatial methods are increasingly used to examine how the context of individuals' lives is associated with behavioral outcomes. These methods require detailed information on where each individual participates in various domains of activity, such as consumption, education, production, and recreation. Calder et al. (2011) used the detailed location data in the LAFANS to create a spatial map of individuals' "activity space." This allows a broader conceptualization of community context, because it is not necessarily tied to the respondent's home (Kwan 2008). This is particularly valuable when individuals spend large amounts of time outside their home neighborhoods. There are significant mechanisms linking context to behavior that occur the area outside where community context is typically measured. While work that is expanding the conceptualization of context has mostly been conducted in developed settings due to the high demands of the spatial data, there is reason to believe these same processes are occurring in rapidly developing urban and peri-urban settings characterized by increasing geographic mobility.

In sum, measures of community context are important for understanding many research questions, but there has been difficulty collecting accurate spatial data on community context features. This difficulty is even more acute in developing settings.

Creating an improved Community Context Instrument

Our research significantly improves the ability to collect community context data, especially in developing settings without numeric address systems. To achieve these improvements, we use two innovative approaches: respondent-focused computer-assisted interface (CAI) design and efficient field-based GIS. The initial prototype was programmed in Microsoft Silverlight, a lightweight application framework that provides easy interface to mapping frameworks, whether online or cached locally. Silverlight applications run within a browser and have very low hardware requirements.

Respondent-focused Computer-Assisted Interface Design

In a CAI approach, usability is a main concern (Couper, 2008, 2000), but frequently the CAI approach is not designed with respondent participation as a primary goal. For some information, it may not be necessary that respondents see data as it is entered or see any visual aids from the interviewer. The recall of spatial data, however, is especially primed and eased by visual aids—most notably maps (Brewer, 1986, 1988; Williams, Healy & Ellis, 1999). For locating community contextual features in settings that do not use numeric address systems, it is important that respondents can view maps and point to locations. Our innovative approach features a CAI interface that dedicates the majority of the display to map visualization. It has been shown that even young children can effectively use maps to navigate and understand their environment (Sandberg & Huttenlocher, 2001; Wiegand, 2006); the more closely a map represents the real world, the better users are able to use them effectively and also recall pertinent information from the map (Downs, 1981; Guelke, 1979; Peterson, Kulhavy, Stock & Pridemore, 1991; Schwartz & Kulhavy, 1981). Satellite imagery, with street overlays, provides graphic detail of buildings, roads, and bodies of water.

We design the interface so respondents can collaboratively complete the community context instrument with the interviewer. The survey methodology literature reports that collaborative, semi-structured data collection approaches can lead to higher data quality when respondents are tasked with activities of high cogitative difficulty (Schober and Conrad 1997). The widely used life history calendar (Freedman et al. 1988) method is an example of a semi-structured approach that usually leads to higher data quality than if questions were asked in a purely structured manner. Our innovation is to design a human-computer interface based on a multi-touch display, which has been shown to be superior to mouse and keyboard for collaborative work (Forlines et al., 2007; Cooperstock et al., 1997). Scrollbars, boxes and buttons, and small-sized controls on the screen require precision movements with a mouse or keyboard, which interrupt collaboration because they are single user input methods. One person has to wait until the other finishes; furthermore, the second user is not always aware what the first user has clicked or typed, which impedes information flow and cognition between users (Shneiderman, 1997; Scott, Shoemaker & Inkpen, 2000). Experiments show that navigating a map interface by touch is more intuitive, faster, and more preferred by users than keyboard or mouse (MacKay et al. 2005; Sears & Shneiderman, 1991), and thus may improve spatial recall. As shown in Figure 1, in our CAI approach, respondents can drag a finger on the screen to scroll the map. In addition, traditional touch functionalities have been extended to multi-touch capabilities that allow users to perform screen interface interactions through gestures such as pinching or expanding two fingers to zoom out or zoom in. Natural gestures in human computer interfaces reduce errors (Burigat et al., 2008) and increase the engagement of the user even on a small screen (Hinckley et al., 2010; Brandl et al., 2008; Yee, 2004). Effective use of multi-touch technology allows a notebook display to maintain the engagement of a respondent much like a large sheet of paper in a traditional collaborative approach, such as has been done with life history calendars. Moreover, multi-touch notebook computers are now widely used consumer technology. The cost premium of a multi-touch device will be minor for most data collection projects.

(Figure 1)

Efficient Field-Based GIS

An additional innovation is an efficient field-based GIS. Our respondent-focused interface requires complex GIS operations and visualizations: e.g., satellite maps are displayed and scrolled at multiple zoom levels. From a computing standpoint, there are high storage and processing costs of these operations. The raster (satellite imagery) map data are multiple gigabytes. Although modern notebooks can easily store these data, processing data in the field in “real time” on a notebook is challenging. The processing must be quick enough so that it doesn’t interfere with collaborative interviewer-respondent interaction, but notebooks cannot quickly process raw gigabytes of satellite data. The traditional way to accomplish these complex GIS tasks is high performance software, such as the ArcGIS suite, but these applications are not feasible for notebooks, nor do they process and visualize spatial data in real time. These applications are well-suited for complex, analytical GIS tasks, but not for a mobile, field-based respondent-focused interface.

To overcome these limitations, we use application development frameworks that have been developed to offload processing costs from the field notebook to remote infrastructure; this is sometimes called “cloud computing.” The notebook simply becomes an input and visualization device. The computer intensive image processing for zooming is performed on a remote computer. When high-speed wireless internet is available, the remote processing is done in real-time and imagery is sent back to the notebook in the field. When wireless internet is not available or too expensive, the processing is done asynchronously: imagery at multiple zoom levels is created in advance on a high performance workstation, stored on the laptop, and “served” locally. This is the approach taken in our field test in Nepal.

Adding Familiar Visual Cues to Aid Recall

In addition to the overhead satellite imagery, we added additional cues to help respondents orient themselves to the map and increase their ability to recall spatial information. We added to the map well-known area landmarks: two airports, several large schools and a college which were well known to respondents, and several dozen intersections or “chowks.” Chowks are a common point of reference and navigation in this setting. The airports and school were added to the maps as icons (an airplane and a yellow school crossing sign, which is used in Nepal). Chowks were labeled on the map in bright yellow text using Nepali script. See Figure 2. The chowk labels were viewable at all levels of map zoom because their text size remained constant, even as the respondent zooms in or out of an area.

(Figure 2)

Choosing to add airports, schools, and chowks were based on our discussions with respondents in the area about what features were most recognizable in this setting. If this approach is used in other contexts, then alternative sets of features could used, such as bodies of water, road features, or neighborhood names—whatever is relevant to the respondents in the setting being studied.

Pilot testing the instrument

Setting

In July and August 2010, we tested the instrument in the study area of the Chitwan Valley Family Study (CVFS). Since 1996, the CVFS has extensively measured social change and family behaviors in the Chitwan Valley of Nepal. The Chitwan Valley is 450 feet above sea level, about 100 miles south-west of Kathmandu, the capital city of Nepal. Chitwan is located in the Terai, a region of low-lying plains along the southern borders of the country. This is an ideal location for testing our instrument. First, the study site is typical of many developing areas and does not use numeric address systems, which makes an excellent location for testing our CAI community context instrument. Second, there is significant community context variability in Chitwan, ranging from urban to very rural, which allows us to test the instrument in area of dense and sparse contextual features. Third, there is a mature research infrastructure in Chitwan with facilities, management personnel, and experienced interviewers. The Institute for Social and Environmental Research (ISER) has conducted high-quality large scale surveys in this population previously, including community contextual measurement. ISER staff helped in the final alterations of the instrument as well as conducting the pilot interviews.

Sample

Given the constraints of a small pilot study, we tested our instrument with a purposive sample of respondents chosen to reflect variations in gender, education, and geographic area within the study site. A total of N=28 individuals interviewed.

Method

The aims of the pilot were to test how respondents were able to use the interface and recall where various contextual features were located using their spatial memories. After approaching a respondent for interview, ISER interviewers briefly explained the purpose of the survey and gave a short introduction in the use of the instrument. Respondents were asked to locate and tap on the map the following features: their own home, the market they typically shop at, the school a household member attends (if applicable), the health post or clinic they typically use, their bank (if applicable), the nearest bus stop, their temple, and their prior home (if they had a previous residence and their previous home was located in the study area). In addition, interviewers asked the following demographic background questions: gender, age, marital status, education, computer ownership and use, and caste.

Interviewers and respondents collaboratively located the respondent's contextual features, although the level of interviewer involvement varied. Some respondents quickly mastered the interface and were able to pan, zoom, and identify features on their own. For these respondents, the interviewer involvement was simply to prompt them on which features to identify (e.g., "Now please locate your bank."). Other respondents needed some help using the zoom functions and map panning, especially at the beginning of an interview, but all respondents shared a significant role using the interface.

As part of the data collection, we collected important measures of interface usability. The first measure was length of interview. Length of interview partly reflects the interface's ease of use, and it is an important metric when considering the feasibility of an instrument. The second usability measure was whether or not the respondent was able to locate his or her home on the map without help. Interviewers started all interviewers at the same level of zoom, with the respondent's home generally in the center. The respondent's home was the first contextual feature he or she was asked to locate. If the respondent could not locate his or her home, the interviewer found it for the respondent and noted that help was needed. Whether or not the respondent needed help is related to the usability of the instrument and the respondent's ability to use overhead satellite maps.

Length of interview, the respondent's ability to use the map to locate his or her home, and the ability to locate other geographic features are important outcomes of success. In addition, the survey research literature predicts important subgroup variation. Prior research shows that individuals who are older, have less education, and have less familiarity with technology are less effective users of computer interfaces (Muilenburg & Berge, 2005). Although the interviewer is always present and respondents do not use the interface on their own, we predicted that older and less educated respondents will take longer to complete the interview and have more difficulty using maps.

Results

The best way to assess improvements in data collection techniques is to determine the most important metrics of usability and data quality and then compare a new method against and existing method in a randomized trial. This approach was not possible in our pilot test, the aim of which was to simply examine initial feasibility. We can report, however, on overall outcomes using our instrument, as well as simple models that assess which subgroups had more and less success using the instrument.

In general, almost all respondents were able to successfully complete the collaborative interview and locate contextual features. Of the 28 respondents, 26 completed the interview. The two respondents who did not complete the interview had little geographic familiarity with the area. One respondent was a young woman from outside the Chitwan area who was visiting her relatives. The other respondent was a woman who had only recently moved to her house (less than three months) and did not have a good geographic grasp of the area. It is likely that these same two respondents would have had difficulty locating contextual features no matter what the instrument (computer or paper, maps or no maps).

(Table 1)

Instrument usability outcomes and demographic characteristics are shown in Table 1 for the N=26 respondents who completed the interview. Usability of the instrument was high for all respondents. Of the 26 respondents, 31% needed assistance locating their home on the map, i.e., the interviewer pointed to the home on the satellite map. After the home was marked on the map, however, it provided a strong spatial memory anchor. There were six subsequent features respondents were asked to locate: markets, schools, health posts, banks, bus stops, and temples (prior homes were not applicable to all respondents and thus are not analyzed here). Interviewers did not offer assistance locating these features: interviewers did assist respondents in using the interface but this was limited to work with the technology. For example, if the respondent said what his or her bank name was, the interviewers were not allowed to help the respondent find that bank. After the respondent's home was marked, the percent of remaining contextual features successfully identified averaged 99%. Of the 26 respondents, 25 of them located all six features. One respondent located only 4 of 6 features (unable to locate a school and temple). Overall, however, the respondents' abilities to use the instrument and orient themselves to satellite maps were remarkably high.

Length of interview varied from a minimum of 6 minutes to a high of 34, with respondents taking on average 16 minutes to complete both the contextual feature identification and simple demographic background survey. Without a comparison to a paper-based instrument or other contextual data collection method, it is hard to interpret these interview length times, but these interview lengths do not appear excessive, especially given the success respondents had using the instruments.

The nearly universal respondent success using the instrument is also encouraging given their backgrounds: education ranged from 6 to 16 years, and fully 35% (the modal category) had <u>never used a computer before in their lives</u>. We don't want to over interpret this finding, but it is compatible with several explanations: perhaps the respondent-focused interface design is able to meet the needs of nearly all users, and/or visual overhead maps is provide powerful spatial memory anchors that are useable even among those with little exposure to technology.

Although the instrument usability was high among all respondents, we did expect variation in length of interview and usability by respondent characteristics, such as education, age, gender, and previous computer use. On a small pilot sample of 26 respondents, we cannot estimate complex statistical model. The sample does, however, meet the minimum rule of thumb of five cases per each predictor variable as recommended by some regression texts (Allison, 1999). We acknowledge that the generalizability of this pilot sample cannot be taken to a larger population. Therefore, we interpret the following models with caution and consider them as suggestions for future, more rigorous statistical tests with a larger sample.

(Table 2)

Table 2 examines predictors of interview length. Given the small sample, we include a subset of background variables covering human capital (education), demographics (gender, age/age-squared), and familiarity with technology (frequency of computer use). We find expected relationships with respondent characteristics. Respondents with more years of education had significantly shorter interview times. Age was also significantly associated with interview times: older respondents took longer. The significant negative quadratic trend of age, however, means that this effect of longer interview times at older ages tended to decrease with age. Being female was not associated with interview length, nor was prior computer use.

(Table 3)

Table 3 examines predictors of respondents needing help to locate their home on the map. This is a binary logistic regression predicting the need for help. We use the same predictors as in the previous model. The only significant predictor is education, again with the expected sign: respondents with more education had lower log odds of needing assistance. Gender, age, and prior computer use was not associated with the outcome.

Discussion

Measurement of concepts at the contextual level is important for testing many hypotheses in the social sciences, but contextual data collection has often been limited, especially in areas that do not use numeric address systems. Respondents often have trouble recalling the exact location of important contextual features, and researchers sometimes rely instead on very imprecise measurement of context (how far away is the feature).

Our instrument addresses these shortcomings with a respondent-focused design that encourages collaboration between interviewer and respondent. The collection of contextual data is a process that benefits from a semi-structured approach (Axinn, Barber, and Ghimire 1997), and our instrument preserves this collaboration even in the presence of computer assisted interviewing techniques.

Although our pilot involved only 28 respondents, there were high levels of success. Twenty six of the 28 successfully completed the interview. Sixty-nine percent of respondent could find their home on the map without any locational assistance. After their home was located, success finding the remaining contextual features averaged 99%, which points to the powerful ability of maps to stimulate spatial memory. This success was observed in a group of respondents with little prior exposure to technology: 35% had never used a computer before in their lives.

From our pilot test, there was at least one unexpected challenge we had not foreseen. Although respondents did not have trouble orienting to the map, several respondents had difficulty using the touch screen: some respondents used the fingernail to touch the screen, which doesn’t work on capacitive technology: fingernails have inadequate electrical conductivity. In addition, when marking a point, some respondents pressed the screen as if making a fingerprint, rather than tapping, which prevented the interface from recording the location. In a population that has little familiarity with iPods and touch screens, in hindsight it is easy to understand these difficulties. We had not appreciated, however, the fact that the simple act of using a touch screen is not as simple as we had thought. Even touching is a learned behavior, and touching a capacitive computer display involved skills that are different than touching other physical objects. Although interviewers helped respondents with the interface, there was not a standardized instruction developed before entering the field. In the future, a brief (1-2 minute) instructional session, with the opportunity for respondents to practice their touching gestures, will be tested and developed.

The results of the pilot suggest several next steps. As the technique is developed, we will need to conduct a formal comparison between our instrument and a different mode of data collection, such as paper-based instrument or one that does not use maps. In addition, the small sample prevents us from generalizing our results to the larger Chitwan population and our statistical results are only suggestive and cannot be a basis for rigorous hypothesis tests about which subgroups will have more and less success using the instrument. Despite these limitations, the overall pattern of results is encouraging and the pilot testing in the field has provided valuable qualitative feedback on how to improve the instrument. We hope to address these challenges in the future using a larger study with a more representative sample and a more rigorous research design.

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Table 1: Descriptive Statistics

	Mean	Std Dev	Minimum	Maximum
Usability Outcomes				
Respondent needed help locating home on map	0.31	0.47	0	1
% of contextual features located by respondent	0.99	0.07	0.67	1
Interview length (minutes)	16.38	7.54	6	34
Respondent Characteristics				
Female	0.46	0.51	0	1
Age	25.96	9.37	13	47
Married	0.50	0.51	0	1
Years of Education	10.42	2.76	6	16
Upper Caste Hindu Caste	0.50	0.51	0	1
Household owns computer	0.35	0.49	0	1
Frequency of computer use				
(Treated as ordinal scale)	1.92	1.62	0	4
(Frequency distribution)				
Never used a computer before	35%			
A few times per year	8%			
A few days per month	8%			
A few days per week	31%			
Every day	19%			

N=26 respondents

Table 2: Linear Regression Predicting Interview Length in Minutes

	Estimate	
Years of Education	-1.01	+
Female	-0.80	
Age	2.89	*
Age-Squared	-0.05	*
Frequency of computer use	-0.87	
Intercept	-9.95	
R-squared	0.37	
N	26	

*p<.05, +p<.10, two-tailed tests

Table 3: Logistic Regression Predicting Needing Help Finding Home

	Estimate	
Years of Education	-0.54	+
Female	-0.79	
Age	0.52	
Age-Squared	-0.01	
Frequency of computer use	-0.03	
Intercept	-2.24	
N	26	

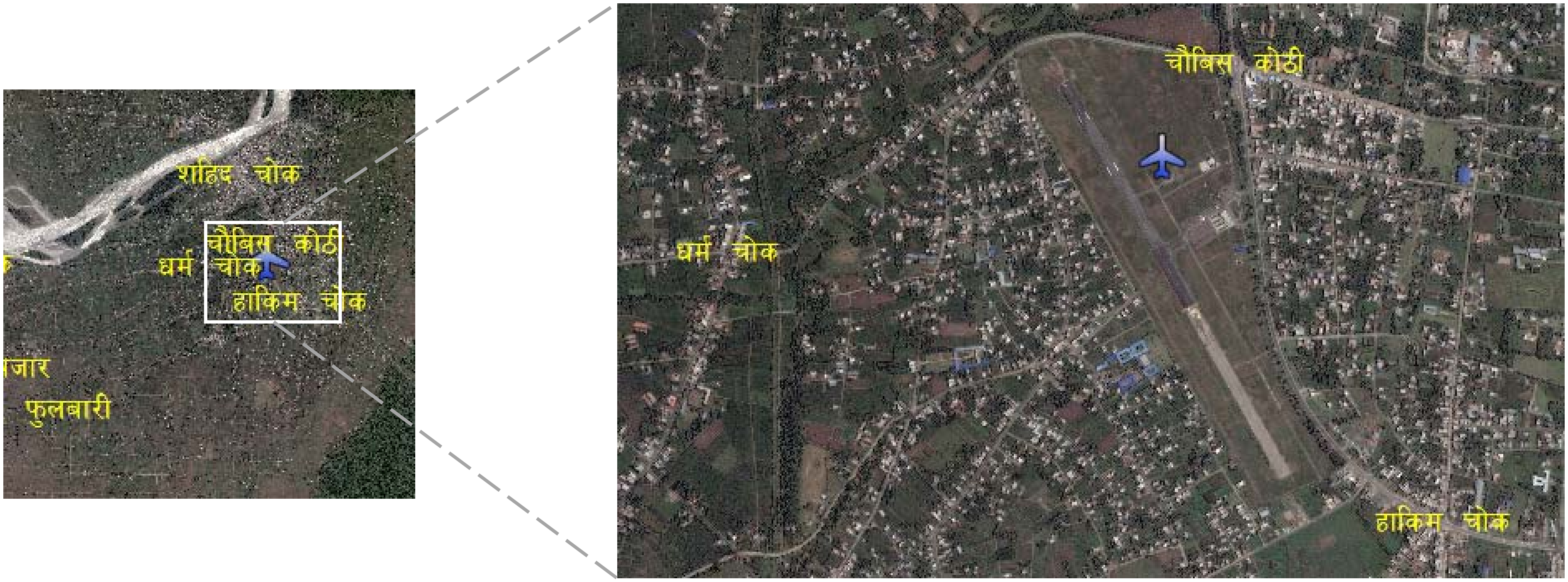
*p<.05, +p<.10, two-tailed tests

Figure 1: A respondent-focused interface design for collecting spatial data

Large buttons are used by finger touch, without mouse or keyboard. This promotes collaboration between interviewer and respondent.

Majority of the screen display area is non-technical and is devoted to map visualization, which also promotes collaboration and respondent involvement.

Figure 2: Chowks (intersections) labeled in yellow Nepali text serve as spatial memory anchors and are viewable at all map zoom levels



Zoom level 12 **Zoom level 15**

Observe how text size remains constant even when map zoom increases. Icon for airport also retains constant size.