Survey Research in HCI

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Short Description of the Method

A survey is a method of gathering information by asking questions to a subset of people, the results of which can be generalized to the wider target population. There are many different types of surveys, many ways to sample a population, and many ways to collect data from that population. Traditionally, surveys have been administered via mail, telephone, or in person. The Internet has become a popular mode for surveys due to the low cost of gathering data, ease and speed of survey administration, and its broadening reach across a variety of populations worldwide. Surveys in human–computer interaction (HCI) research can be useful to:

- Gather information about people's habits, interaction with technology, or behavior
- Get demographic or psychographic information to characterize a population
- Get feedback on people's experiences with a product, service, or application
- Collect people's attitudes and perceptions toward an application in the context of usage
- Understand people's intents and motivations for using an application
- Quantitatively measure task success with specific parts of an application
- Capture people's awareness of certain systems, services, theories, or features
- Compare people's attitudes, experiences, etc. over time and across dimensions

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While powerful for specific needs, surveys do not allow for observation of the respondents' context or follow-up questions. When conducting research into precise behaviors, underlying motivations, and the usability of systems, then other research methods may be more appropriate or needed as a complement.

This chapter reviews the history of surveys and appropriate uses of surveys and focuses on the best practices in survey design and execution.

History, Intellectual Tradition, Evolution

Since ancient times, societies have measured their populations via censuses for food planning, land distribution, taxation, and military conscription. Beginning in the nineteenth century, political polling was introduced in the USA to project election results and to measure citizens' sentiment on a range of public policy issues. At the emergence of contemporary psychology, Francis Galton pioneered the use of questionnaires to investigate the nature vs. nurture debate and differences between humans, the latter of which evolved into the field of psychometrics (Clauser, 2007). More recently, surveys have been used in HCI research to help answer a variety of questions related to people's attitudes, behaviors, and experiences with technology.

Though nineteenth-century political polls amplified public interest in surveys, it was not until the twentieth century that meaningful progress was made on survey-sampling methods and data representativeness. Following two incorrect predictions of the US presidential victors by major polls (Literary Digest for Landon in 1936 and Gallup for Dewey in 1948), sampling methods were assailed for misrepresenting the US electorate. Scrutiny of these polling failures; persuasive academic work by statisticians such as Kiaer, Bowley, and Neyman; and extensive experimentation by the US Census Bureau led to the acceptance of random sampling as the gold standard for surveys (Converse, 1987).

Roughly in parallel, social psychologists aimed to minimize questionnaire biases and optimize data collection. For example, in the 1920s and 1930s, Louis Thurstone and Rensis Likert demonstrated reliable methods for measuring attitudes (Edwards & Kenney, 1946); Likert's scaling approach is still widely used by survey practitioners. Stanley Payne's, 1951 classic "The Art of Asking Questions" was an early study of question wording. Subsequent academics scrutinized every aspect of survey design. Tourangeau (1984) articulated the four cognitive steps to survey responses, noting that people have to comprehend what is asked, retrieve the appropriate information, judge that information according to the question, and map the judgement onto the provided responses. Krosnick & Fabrigar (1997) studied many components of questionnaire design, such as scale length, text labels, and "no opinion" responses. Groves (1989) identified four types of survey-related error: coverage, sampling, measurement, and non-response. As online surveys grew in popularity, Couper (2008) and others studied bias from the visual design of Internet questionnaires.

The use of surveys for HCI research certainly predates the Internet, with efforts to understand users' experiences with computer hardware and software. In 1983, researchers at Carnegie Mellon University conducted an experiment comparing

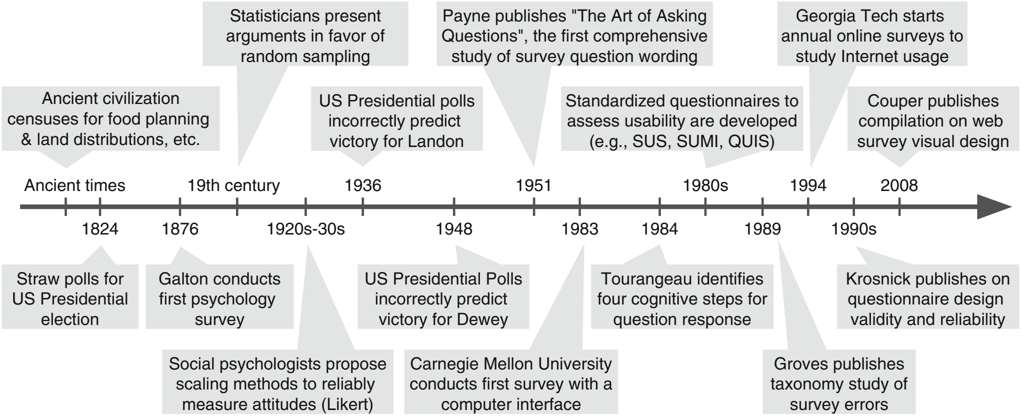

Ancient civilization censuses for food planning & land distributions, etc.
Statisticians present arguments in favor of random sampling
US Presidential polls incorrectly predict victory for Landon
Payne publishes "The Art of Asking Questions", the first comprehensive study of survey question wording
Standardized questionnaires to assess usability are developed (e.g., SUS, SUMI, QUIS)
Georgia Tech starts annual online surveys to study Internet usage
Couper publishes compilation on web survey visual design
Ancient times
19th century
1936
1951
1980s
1994
2008
1824
1876
1920s-30s
1948
1983
1984
1989
1990s
Straw polls for US Presidential election
Galton conducts first psychology survey
Social psychologists propose scaling methods to reliably measure attitudes (Likert)
US Presidential Polls incorrectly predict victory for Dewey
Carnegie Mellon University conducts first survey with a computer interface
Tourangeau identifies four cognitive steps for question response
Groves publishes taxonomy study of survey errors
Krosnick publishes on questionnaire design validity and reliability

Fig. 1 Summary of the key stages in survey history

computer-collected survey responses with those from a printed questionnaire, finding less socially desirable responses in the digital survey and longer open-ended responses than in the printed questionnaire (Kiesler & Sproull, 1986). With the popularization of graphical user interfaces in the 1980s, surveys joined other methods for usability research. Several standardized questionnaires were developed to assess usability (e.g., SUS, QUIS, SUMI, summarized later in this chapter). Surveys are a direct means of measuring satisfaction; along with efficiency and effectiveness, satisfaction is a pillar of the ISO 9241, part 11, definition of usability (Abran et al., 2003). User happiness is fundamental to Google's HEART framework for user-centric measurement of Web applications (Rodden, Hutchinson, & Fu, 2010). In 1994, the Georgia Institute of Technology started annual online surveys to understand Internet usage and users and to explore Web-based survey research (Pitkow & Recker, 1994). As the Internet era progressed, online applications widely adopted surveys to measure users' satisfaction, unaddressed needs, and problems experienced, in addition to user profiling. See a summary of key stages in survey history in Fig. 1.

What Questions the Method Can Answer

When used appropriately, surveys can help inform application and user research strategies and provide insights into users' attitudes, experiences, intents, demographics, and psychographic characteristics. However, surveys are not the most appropriate method for many other HCI research goals. Ethnographic interviews, log data analysis, card sorts, usability studies, and other methods may be more appropriate. In some cases, surveys can be used with other research methods to holistically inform HCI development. This section explains survey appropriateness, when to avoid using surveys, as well as how survey research can complement other research methods.

When Surveys Are Appropriate

Overall, surveys are appropriate when needing to represent an entire population, to measure differences between groups of people, and to identify changes over time in people's attitudes and experiences. Below are examples of how survey data can be used in HCI research.

Attitudes. Surveys can accurately measure and reliably represent attitudes and perceptions of a population. While qualitative studies are able to gather attitudinal data, surveys provide statistically reliable metrics, allowing researchers to benchmark attitudes toward an application or an experience, to track changes in attitudes over time, and to tie self-reported attitudes to actual behavior (e.g., via log data). For example, surveys can be used to measure customer satisfaction with online banking immediately following their experiences.

Intent. Surveys can collect peoples' reasons for using an application at a specific time, allowing researchers to gauge the frequency across different objectives. Unlike other methods, surveys can be deployed while a person is actually using an application (i.e., an online intercept survey), minimizing the risk of imperfect recall on the respondent's part. Note that specific details and the context of one's intent may not be fully captured in a survey alone. For example, "Why did you visit this website?" could be answered in a survey, but qualitative research may be more appropriate in determining how well one understood specific application elements and what users' underlying motivations are in the context of their daily lives.

Task success. Similar to measuring intent, while HCI researchers can qualitatively observe task success through a lab or a field study, a survey can be used to reliably quantify levels of success. For example, respondents can be instructed to perform a certain task, enter results of the task, and report on their experiences while performing the task.

User experience feedback. Collecting open-ended feedback about a user's experience can be used to understand the user's interaction with technology or to inform system requirements and improvements. For example, by understanding the relative frequency of key product frustrations and benefits, project stakeholders can make informed decisions and trade-offs when allocating resources.

User characteristics. Surveys can be used to understand a system's users and to better serve their needs. Researchers can collect users' demographic information, technographic details such as system savviness or overall tech savviness, and psychographic variables such as openness to change and privacy orientation. Such data enables researchers to discover natural segments of users who may have different needs, motivations, attitudes, perceptions, and overall user experiences.

Interactions with technology. Surveys can be used to understand more broadly how people interact with technology and how technology influences social interactions with others by asking people to self-report on social, psychological, and demographic variables while capturing their behaviors. Through the use of surveys, HCI researchers can glean insights into the effects technology has on the general population.

Awareness. Surveys can also help in understanding people's awareness of existing technologies or specific application features. Such data can, for example, help researchers determine whether low usage with an application is a result of poor awareness or other factors, such as usability issues. By quantifying how aware or unaware people are, researchers can decide whether efforts (e.g., marketing campaigns) are needed to increase overall awareness and thus use.

Comparisons. Surveys can be used to compare users' attitudes, perceptions, and experiences across user segments, time, geographies, and competing applications and between experimental and control versions. Such data enable researchers to explore whether user needs and experiences vary across geographies, assess an application's strengths and weaknesses among competing technologies and how each compares with their competitors' applications, and evaluate potential application improvements while aiding decision making between a variety of proposed designs.

When to Avoid Using a Survey

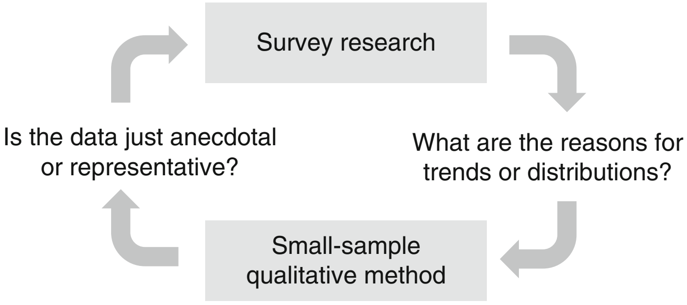
Because surveys are inexpensive and easy to deploy compared to other methods, many people choose survey research even when it is inappropriate for their needs. Such surveys can produce invalid or unreliable data, leading to an inaccurate understanding of a population and poor user experiences. Below are some HCI research needs that are better addressed with other methods.

Precise behaviors. While respondents can be asked to self-report their behaviors, gathering this information from log data, if available, will always be more accurate. This is particularly true when trying to understand precise user behaviors and flows, as users will struggle to recall their exact sequence of clicks or specific pages visited. For behaviors not captured in log data, a diary study, observational study, or experience sampling may gather more accurate results than a survey.

Underlying motivations. People often do not understand or are unable to explain why they take certain actions or prefer one thing over another. Someone may be able to report their intent in a survey but may not be aware of their subconscious motivations for specific actions. Exploratory research methods such as ethnography or contextual inquiry may be more appropriate than directly asking about underlying motivations in a survey.

Usability evaluations. Surveys are inappropriate for testing specific usability tasks and understanding of tools and application elements. As mentioned above, surveys can measure task success but may not explain why people cannot use a particular application, why they do not understand some aspect of a product, or why they do not identify missteps that caused the task failure. Furthermore, a user may still be able to complete a given task even though he or she encountered several confusions, which could not be uncovered through a survey. Task-based observational research and interview methods, such as usability studies, are better suited for such research goals.

Fig. 2 Employing survey research either before or after research using other methods


Survey research
What are the reasons for trends or distributions?
Small-sample qualitative method
Is the data just anecdotal or representative?

Using Surveys with Other Methods

Survey research may be especially beneficial when used in conjunction with other research methods (see Fig. 2). Surveys can follow previous qualitative studies to help quantify specific observations. For many surveys, up-front qualitative research may even be required to inform its content if no previous research exists. On the other hand, surveys can also be used to initially identify high-level insights that can be followed by in-depth research through more qualitative (meaning smaller sample) methods.

For example, if a usability study uncovers a specific problem, a survey can quantify the frequency of that problem across the population. Or a survey can be used first to identify the range of frustrations or goals, followed by qualitative interviews and observational research to gain deeper insights into self-reported behaviors and sources of frustration. Researchers may interview survey respondents to clarify responses (e.g., Yew, Shamma, & Churchill, 2011), interview another pool of participants in the same population for comparison (e.g., Froelich et al., 2012), or interview both survey respondents and new participants (e.g., Archambault & Grudin, 2012).

Surveys can also be used in conjunction with A/B experiments to aid comparative evaluations. For example, when researching two different versions of an application, the same survey can be used to assess both. By doing this, differences in variables such as satisfaction and self-reported task success can be measured and analyzed in parallel with behavioral differences observed in log data. Log data may show that one experimental version drives more traffic or engagement, but the survey may show that users were less satisfied or unable to complete a task. Moreover, log data can further validate insights from a previously conducted survey. For example, a social recommendation study by Chen, Geyer, Dugan, Muller, and Guy (2009) tested the quality of recommendations first in a survey and then through logging in a large field deployment. Psychophysiological data may be another objective accompaniment to survey data. For example, game researchers have combined surveys with data such as facial muscle and electrodermal activity (Nacke, Grimshaw, & Lindley, 2010) or attention and meditation as measured with EEG sensors (Schild, LaViola, & Masuch, 2012).

How to Do It: What Constitutes Good Work

This section breaks down survey research into the following six stages:

1. Research goals and constructs
2. Population and sampling
3. Questionnaire design and biases
4. Review and survey pretesting
5. Implementation and launch
6. Data analysis and reporting

Research Goals and Constructs

Before writing survey questions, researchers should first think about what they intend to measure, what kind of data needs to be collected, and how the data will be used to meet the research goals. When the survey-appropriate *research goals* have been identified, they should be matched to *constructs*, i.e., unidimensional attributes that cannot be directly observed. The identified constructs should then be converted into one or multiple survey questions. Constructs can be identified from prior primary research or literature reviews. Asking multiple questions about the same construct and analyzing the responses, e.g., through factor analysis, may help the researcher ensure the construct's validity.

An example will illustrate the process of converting constructs into questions. An overarching research goal may be to understand users' happiness with an online application, such as Google Search, a widely used Web search engine. Since happiness with an application is often multidimensional, it is important to separate it into measurable pieces—its constructs. Prior research might indicate that constructs such as "overall satisfaction," "perceived speed," and "perceived utility" contribute to users' happiness with that application. When all the constructs have been identified, survey questions can be designed to measure each. To validate each construct, it is important to evaluate its unique relationship with the higher level goal, using correlation, regression, factor analysis, or other methods. Furthermore, a technique called *cognitive pretesting* can be used to determine whether respondents are interpreting the constructs as intended by the researcher (see more details in the pretesting section).

Once research goals and constructs are defined, there are several other considerations to help determine whether a survey is the most appropriate method and how to proceed:

- Do the survey constructs focus on results which will directly address research goals and inform stakeholders' decision making rather than providing merely informative data? An excess of "nice-to-know" questions increases survey length and the likelihood that respondents will not complete the questionnaire, diminishing the effectiveness of the survey results.

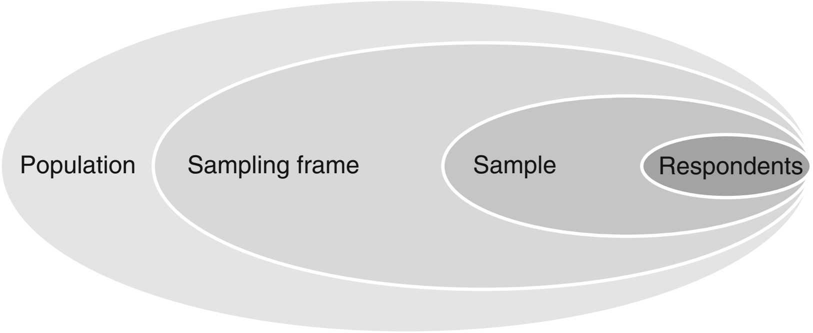


Fig. 3 The relationship between population, sampling frame, sample, and respondents

- Will the results be used for longitudinal comparisons or for one-time decisions? For longitudinal comparisons, researchers must plan on multiple survey deployments without exhausting available respondents.
- What is the number of responses needed to provide the appropriate level of precision for the insights needed? By calculating the number of responses needed (as described in detail in the following section), the researcher will ensure that key metrics and comparisons are statistically reliable. Once the target number is determined, researchers can then determine how many people to invite.

Population and Sampling

Key to effective survey research is determining who and how many people to survey. In order to do this, the survey's *population*, or set of individuals that meet certain criteria, and to whom researchers wish to generalize their results must first be defined. Reaching everyone in the population (i.e., a census) is typically impossible and unnecessary. Instead, researchers approximate the true population by creating a *sampling frame*, i.e., the set of people who the researcher is able to contact for the survey. The perfect sampling frame is identical to the population, but often a survey's sampling frame is only a portion of the population. The people from the sampling frame who are invited to take the survey are the *sample*, but only those who answer are *respondents*. See Fig. 3 illustrating these different groups.

For example, a survey can be deployed to understand the satisfaction of a product's or an application's users. In this case, the population includes everyone that uses the application, and the sampling frame consists of users that are actually reachable. The sampling frame may exclude those who have abandoned the application, anonymous users, and users who have not opted in to being contacted for research. Though the sampling frame may exclude many users, it could still include far more people than are needed to collect a statistically valid number of responses. However, if the sampling frame systematically excludes certain types of people (e.g., very dissatisfied or disengaged users), the survey will suffer from *coverage error* and its responses will misrepresent the population.

Probability Versus Non-probability Sampling

Sampling a population can be accomplished through probability- and non-probability-based methods. *Probability or random sampling* is considered the gold standard because every person in the sampling frame has an equal, nonzero chance of being chosen for the sample; essentially, the sample is selected completely randomly. This minimizes *sampling bias*, also known as *selection bias*, by randomly drawing the sample from individuals in the sampling frame and by inviting everyone in the sample in the same way. Examples of probability sampling methods include random digit telephone dialing, address-based mail surveys utilizing the US Postal Service Delivery Sequence File (DSF), and the use of a panel recruited through random sampling, those who have agreed in advance to receive surveys. For Internet surveys in particular, methods allowing for random sampling include intercept surveys for those who use a particular product (e.g., pop-up surveys or in-product links), list-based samples (e.g., for e-mail invitations), and pre-recruited probability-based panels (see Couper, 2000, for a thorough review). Another way to ensure probability sampling is to use a preexisting sampling frame, i.e., a list of candidates previously assembled using probability sampling methods. For example, Shklovski, Kraut, and Cummings' (2008) study of the effect of residential moves on communication with friends was drawn from a publicly available, highly relevant sampling frame, the National Change of Address (NCOA) database. Another approach is to analyze selected subsets of data from an existing representative survey like the General Social Survey (e.g., Wright & Randall, 2012).

While probability sampling is ideal, it is often impossible to reach and randomly select from the entire target population, especially when targeting small populations (e.g., users of a specialized enterprise product or experts in a particular field) or investigating sensitive or rare behavior. In these situations, researchers may use *non-probability sampling* methods such as volunteer opt-in panels, unrestricted self-selected surveys (e.g., links on blogs and social networks), snowball recruiting (i.e., asking for friends of friends), and *convenience samples* (i.e., targeting people readily available, such as mall shoppers) (Couper, 2000). However, non-probability methods are prone to high sampling bias and hence reduce representativeness compared to random sampling. One way representativeness can be assessed is by comparing key characteristics of the target population with those from the actual sample (for more details, refer to the analysis section).

Many academic surveys use convenience samples from an existing pool of the university's psychology students. Although not representative of most Americans, this type of sample is appropriate for investigating technology behavior among young people such as sexting (Drouin & Landgraff, 2012; Weisskirch & Delevi, 2011), instant messaging (Anandarajan, Zaman, Dai, & Arinze, 2010; Junco & Cotten, 2011; Zaman et al., 2010), and mobile phone use (Auter, 2007; Harrison, 2011; Turner, Love, & Howell, 2008). Convenience samples have also been used to identify special populations. For example, because identifying HIV and tuberculosis patients through official lists of names is difficult because of patient confidentiality, one study about the viability of using cell phones and text messages in HIV and tuberculosis education handed out surveys to potential respondents in health clinic waiting rooms (Person, Blain, Jiang, Rasmussen, & Stout, 2011). Similarly, a study of Down's syndrome patients' use of computers invited participation through special interest listservs (Feng, Lazar, Kumin, & Ozok, 2010).

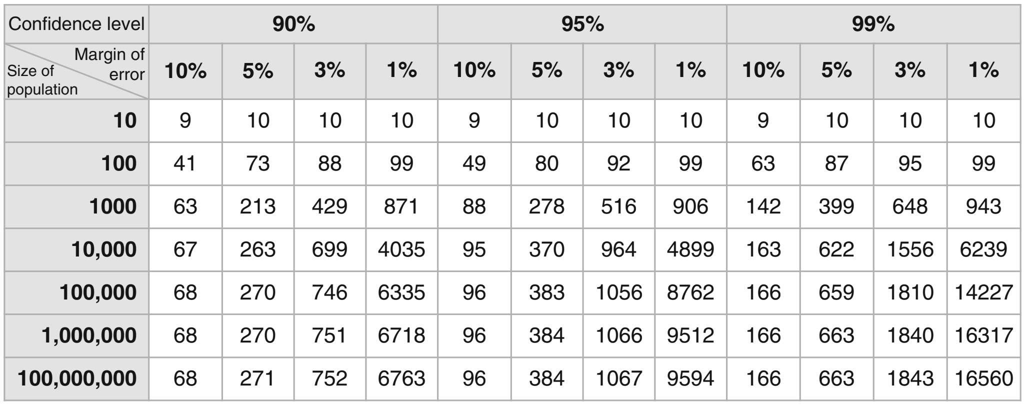
Determining the Appropriate Sample Size

No matter which sampling method is used, it is important to carefully determine the target sample size for the survey, i.e., the number of survey responses needed. If the sample size is too small, findings from the survey cannot be accurately generalized to the population and may fail to detect generalizable differences between groups. If the sample is larger than necessary, too many individuals are burdened with taking the survey, analysis time for the researcher may increase, or the sampling frame is used up too quickly. Hence, calculating the optimal sample size becomes crucial for every survey.

First, the researcher needs to determine approximately how many people make up the population being studied. Second, as the survey does not measure the entire population, the required level of precision must be chosen, which consists of the margin of error and the confidence level. The *margin of error* expresses the amount of sampling error in the survey, i.e., the range of uncertainty around an estimate of a population measure, assuming normally distributed data. For example, if 60 % of the sample claims to use a tablet computer, a 5 % margin of error would mean that actually 55–65 % of the population use tablet computers. Commonly used margin of errors are 5 and 3 %, but depending on the goals of the survey anywhere between 1 and 10 % may be appropriate. Using a margin of error higher than 10 % is not recommended, unless a low level of precision can meet the survey's goals. The *confidence level* indicates how likely the reported metric falls within the margin of error if the study were repeated. A 95 % confidence level, for example, would mean that 95 % of the time, observations from repeated sampling will fall within the interval defined by the margin of error. Commonly used confidence levels are 99, 95, and 90 %; using less than 90 % is not recommended.

There are various formulas for calculating the target sample size. Figure 4, based on Krejcie and Morgan's formula (1970), shows the appropriate sample size, given the population size, as well as the chosen margin of error and confidence level for your survey. Note that the table is based on a population proportion of 50 % for the response of interest, the most cautious estimation (i.e., when higher or lower than 50 %, the required sample size declines to achieve the same margin of error). For example, for a population larger than 100,000, a sample size of 384 is required to achieve a confidence level of 95 % and a margin of error of 5 %. Note that for population sizes over about 20,000, the required sample size does not significantly increase. Researchers may set the sample size to 500 to estimate a single population parameter, which yields a margin of error of about ±4.4 % at a 95 % confidence level for large populations.

After having determined the target sample size for the survey, the researcher now needs to work backwards to estimate the number of people to actually invite to the



Confidence level	90%				95%				99%			
Margin of error / Size of population	10%	5%	3%	1%	10%	5%	3%	1%	10%	5%	3%	1%
10	9	10	10	10	9	10	10	10	9	10	10	10
100	41	73	88	99	49	80	92	99	63	87	95	99
1000	63	213	429	871	88	278	516	906	142	399	648	943
10,000	67	263	699	4035	95	370	964	4899	163	622	1556	6239
100,000	68	270	746	6335	96	383	1056	8762	166	659	1810	14227
1,000,000	68	270	751	6718	96	384	1066	9512	166	663	1840	16317
100,000,000	68	271	752	6763	96	384	1067	9594	166	663	1843	16560

Fig. 4 Sample size as a function of population size and accuracy (confidence level and margin of error)

survey, taking into account the estimated size for each subgroup and the expected response rate. If a subgroup's incidence is very small, the total number of invitations must be increased to ensure the desired sample size for this subgroup. The *response rate* of a survey describes the percentage of those who completed the survey out of all those that were invited (for more details, see the later sections on monitoring survey paradata and maximizing response rates). If a similar survey has been conducted before, then its response rate is a good reference point for calculating the required sample size. If there is no prior response rate information, the survey can be sent out to a small number of people first to measure the response rate, which is then used to determine the total number of required invitations.

For example, assuming a 30 % response rate, a 50 % incidence rate for the group of interest, and the need for 384 complete responses from that group, 2,560 people should be invited to the survey. At this point, the calculation may determine that the researcher may require a sample that is actually larger than the sampling frame; hence, the researcher may need to consider more qualitative methods as an alternative.

Mode and Methods of Survey Invitation

To reach respondents, there are four basic survey modes: mail or written surveys, phone surveys, face-to-face or in-person surveys, and Internet surveys. Survey modes may also be used in combination. The survey mode needs to be chosen carefully as each mode has its own advantages and disadvantages, such as differences in typical response rates, introduced biases (Groves, 1989), required resources and costs, audience that can be reached, and respondents' level of anonymity.

Today, many HCI-related surveys are Internet based, as benefits often outweigh their disadvantages. Internet surveys have the following major advantages:

- Easy access to large geographic regions (including international reach)
- Simplicity of creating a survey by leveraging easily accessible commercial tools

- Cost savings during survey invitation (e.g., no paper and postage, simple implementation, insignificant cost increase for large sample sizes) and analysis (e.g., returned data is already in electronic format)
- Short fielding periods, as the data is collected immediately
- Lower bias due to respondent anonymity, as surveys are self-administered with no interviewer present
- Ability to customize the questionnaire to specific respondent groups using skip logic (i.e., asking respondents a different set of questions based on the answer to a previous question)

Internet surveys also have several disadvantages. The most discussed downside is the introduction of *coverage error*, i.e., a potential mismatch between the target population and the sampling frame (Couper, 2000; Groves, 1989). For example, online surveys fail to reach people without Internet or e-mail access. Furthermore, those invited to Internet surveys may be less motivated to respond or to provide accurate data because such surveys are less personal and can be ignored more easily. This survey mode also relies on the respondents' ability to use a computer and may only provide the researcher with minimal information about the survey respondents. (See chapter on "Crowdsourcing in HCI Research.")

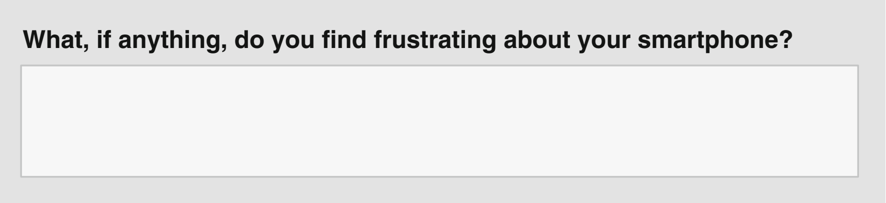
Questionnaire Design and Biases

Upon establishing the constructs to be measured and the appropriate sampling method, the first iteration of the survey questionnaire can be designed. It is important to carefully think through the design of each survey question (first acknowledged by Payne, 1951), as it is fairly easy to introduce biases that can have a substantial impact on the reliability and validity of the data collected. Poor questionnaire design may introduce *measurement error*, defined as the deviation of the respondents' answers from their true values on the measure. According to Couper (2000), measurement error in self-administered surveys can arise from the respondent (e.g., lack of motivation, comprehension problems, deliberate distortion) or from the instrument (e.g., poor wording or design, technical flaws). In most surveys, there is only one opportunity to deploy, and unlike qualitative research, no clarification or probing is possible. For these reasons, it is crucial that the questions accurately measure the constructs of interest.

Going forward, this section covers different types of survey questions, common questionnaire biases, questions to avoid, visual design considerations, reuse of established questionnaires, as well as visual survey design considerations.

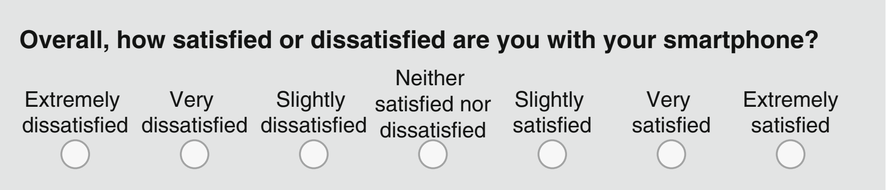
Types of Survey Questions

There are two categories of survey questions—open- and closed-ended questions. Open-ended questions (Fig. 5) ask survey respondents to write in their own answers, whereas closed-ended questions (Fig. 6) provide a set of predefined answers to choose from.



What, if anything, do you find frustrating about your smartphone?

Fig. 5 Example of a typical open-ended question



Overall, how satisfied or dissatisfied are you with your smartphone?

Extremely dissatisfied	Very dissatisfied	Slightly dissatisfied	Neither satisfied nor dissatisfied	Slightly satisfied	Very satisfied	Extremely satisfied
○	○	○	○	○	○	○

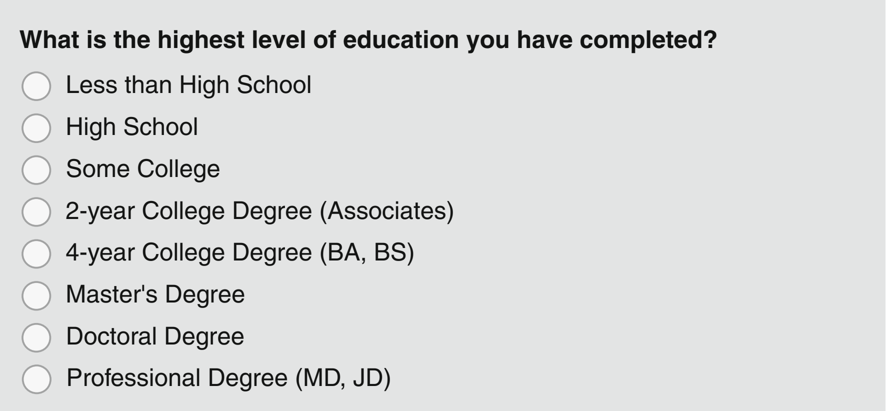
Fig. 6 Example of a typical closed-ended question, a bipolar rating question in particular

Open-ended questions are appropriate when:

- The universe of possible answers is unknown, e.g., “What is your favorite smartphone application?”. However, once the universe of possible answers is identified, it may be appropriate to create a closed-ended version of the same question.
- There are so many options in the full list of possible answers that they cannot be easily displayed, e.g., “Which applications have you used on your smartphone in the last week?”.
- Measuring quantities with natural metrics (i.e., a construct with an inherent unit of measurement, such as age, length, or frequency), when being unable to access information from log data, such as time, frequency, and length, e.g., “How many times do you use your tablet in a typical week?” (using a text field that is restricted to numeric input, the answers to which can later be bucketed flexibly).
- Measuring qualitative aspects of a user’s experience, e.g., “What do you find most frustrating about using your smartphone?”.

Closed-ended questions are appropriate when:

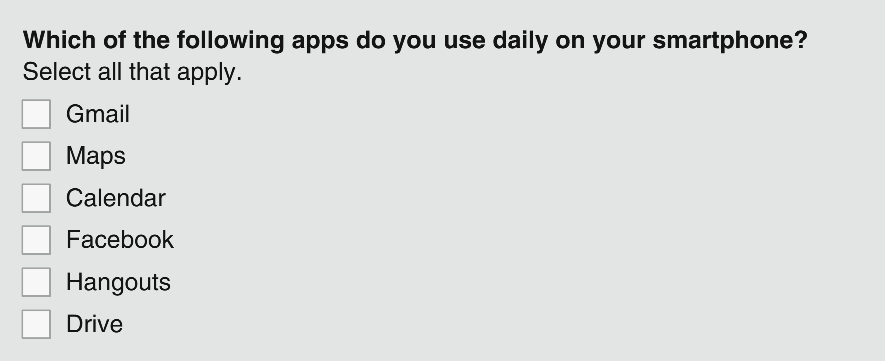
- The universe of possible answers is known and small enough to be easily provided, e.g., “Which operating system do you use on your smartphone?” (with answer options including “Android” and “iOS”).
- Rating a single object on a dimension, e.g., “Overall, how satisfied or dissatisfied are you with your smartphone?” (on a 7-point scale from “Extremely dissatisfied” to “Extremely satisfied”).
- Measuring quantities without natural metrics, such as importance, certainty, or degree, e.g., “How important is it to have your smartphone within reach 24 h a day?” (on a 5-point scale from “Not at all important” to “Extremely important”).



What is the highest level of education you have completed?

○ Less than High School
○ High School
○ Some College
○ 2-year College Degree (Associates)
○ 4-year College Degree (BA, BS)
○ Master's Degree
○ Doctoral Degree
○ Professional Degree (MD, JD)

Fig. 7 Example of a single-choice question



Which of the following apps do you use daily on your smartphone?
Select all that apply.

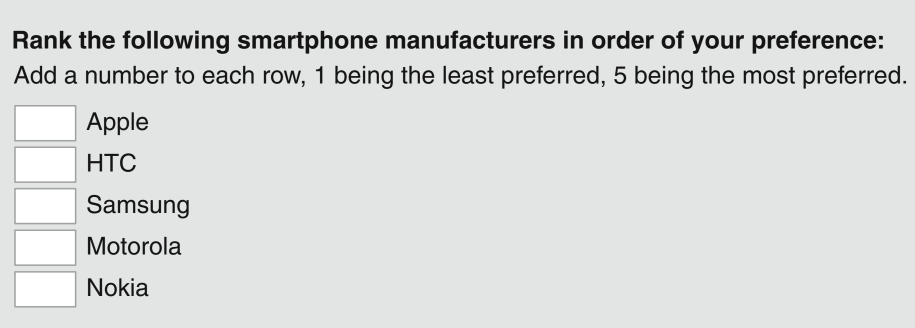
□ Gmail
□ Maps
□ Calendar
□ Facebook
□ Hangouts
□ Drive

Fig. 8 Example of a multiple-choice question

Types of Closed-Ended Survey Questions

There are four basic types of closed-ended questions: single-choice, multiple-choice, rating, and ranking questions.

1. *Single-choice questions* work best when only one answer is possible for each respondent in the real world (Fig. 7).
2. *Multiple-choice questions* are appropriate when more than one answer may apply to the respondent. Frequently, multiple-choice questions are accompanied by "select all that apply" help text. The maximum number of selections may also be specified to force users to prioritize or express preferences among the answer options (Fig. 8).
3. *Ranking questions* are best when respondents must prioritize their choices given a real-world situation (Fig. 9).
4. *Rating questions* are appropriate when the respondent must judge an object on a continuum. To optimize reliability and minimize bias, scale points need to be

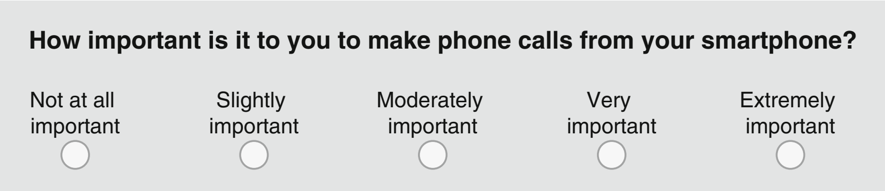


Rank the following smartphone manufacturers in order of your preference:

Add a number to each row, 1 being the least preferred, 5 being the most preferred.

□ Apple
□ HTC
□ Samsung
□ Motorola
□ Nokia

Fig. 9 Example of a ranking question



How important is it to you to make phone calls from your smartphone?

Not at all important ○	Slightly important ○	Moderately important ○	Very important ○	Extremely important ○

Fig. 10 Example of a rating question, for a unipolar construct in particular

fully labeled instead of using numbers (Groves et al., 2004), and each scale point should be of equal width to avoid bias toward visually bigger response options (Tourangeau, Couper, & Conrad, 2004). Rating questions should use either a unipolar or a bipolar scale, depending on the construct being measured (Krosnick & Fabrigar, 1997; Schaeffer & Presser, 2003).

Unipolar constructs range from zero to an extreme amount and do not have a natural midpoint. They are best measured with a 5-point rating scale (Krosnick & Fabrigar, 1997), which optimizes reliability while minimizing respondent burden, and with the following scale labels, which have been shown to be semantically equidistant from each other (Rohrmann, 2003): "Not at all …," "Slightly …," "Moderately …," "Very …," and "Extremely …." Such constructs include importance (see Fig. 10), interest, usefulness, and relative frequency. *Bipolar constructs* range from an extreme negative to an extreme positive with a natural midpoint. Unlike unipolar constructs, they are best measured with a 7-point rating scale to maximize reliability and data differentiation (Krosnick & Fabrigar, 1997). Bipolar constructs may use the following scale labels: "Extremely …," "Moderately …," "Slightly …," "Neither … nor …," "Slightly …," "Moderately …," and "Extremely …." Such constructs include satisfaction (see Fig. 6, from dissatisfied to satisfied), perceived speed (from slow to fast), ease of use (from difficult to easy), and visual appeal (from unappealing to appealing).

When using a rating scale, the inclusion of a midpoint should be considered. While some may argue that including a midpoint provides an easy target for respondents who shortcut answering questions, others argue that the exclusion of a midpoint forces people who truly are in the middle to choose an option that does not reflect their actual opinion. O'Muircheartaigh, Krosnick, and Helic (2001) found that having a midpoint on a rating scale increases reliability, has no effect on validity, and does not result in lower data quality. Additionally, people who look for shortcuts ("shortcutters") are not more likely to select the midpoint when present. Omitting the midpoint, on the other hand, increases the amount of random measurement error, resulting in those who actually feel neutral to end up making a random choice on either side of the scale. These findings suggest that a midpoint should be included when using a rating scale.

Questionnaire Biases

After writing the first survey draft, it is crucial to check the phrasing of each question for potential biases that may bias the responses. The following section covers five common questionnaire biases: satisficing, acquiescence bias, social desirability, response order bias, and question order bias.

Satisficing

Satisficing occurs when respondents use a suboptimal amount of cognitive effort to answer questions. Instead, satisficers will typically pick what they consider to be the first acceptable response alternative (Krosnick, 1991; Simon, 1956). Satisficers compromise one or more of the following four cognitive steps for survey response as identified by Tourangeau (1984):

1. *Comprehension* of the question, instructions, and answer options
2. *Retrieval* of specific memories to aid with answering the question
3. *Judgement* of the retrieved information and its applicability to the question
4. *Mapping* of judgement onto the answer options

Satisficers shortcut this process by exerting less cognitive effort or by skipping one or more steps entirely; satisficers use less effort to understand the question, to thoroughly search their memories, to carefully integrate all retrieved information, or to accurately pick the proper response choice (i.e., they pick the next best choice).

Satisficing can take weak and strong forms (Krosnick, 1999). Weak satisficers make an attempt to answer correctly yet are less than thorough, while strong satisficers may not at all search their memory for relevant information and simply select answers at random in order to complete the survey quickly. In other words, weak satisficers carelessly process all four cognitive steps, while strong satisficers typically skip the retrieval and judgement steps.

Respondents are more likely to satisfice when (Krosnick, 1991):

- Cognitive ability to answer is low.
- Motivation to answer is low.
- Question difficulty is high at one of the four stages, resulting in cognitive exertion.

To minimize satisficing, the following may be considered:

- Complex questions that require an inordinate amount of cognitive exertion should be avoided.
- Answer options such as “no opinion,” “don’t know,” “not applicable,” or “unsure” should be avoided, since respondents with actual opinions will be tempted and select this option (Krosnick, 2002; Schaeffer & Presser, 2003). Instead, respondents should first be asked whether they have thought about the proposed question or issue enough to have an opinion; those that haven’t should be screened out.
- Using the same rating scale in a series of back-to-back questions should be avoided. Potential satisfiers may pick the same scale point for all answer options. This is known as straight-lining or item non-differentiation (Herzog & Bachman, 1981; Krosnick & Alwin, 1987, 1988).
- Long questionnaires should be avoided, since respondents will be less likely to optimally answer questions when they become increasingly fatigued and unmotivated (Cannell & Kahn, 1968; Herzog & Bachman, 1981).
- Respondent motivation can be increased by explaining the importance of the survey topic and that their responses are critical to the researcher (Krosnick, 1991).
- Respondents may be asked to justify their answer to the question that may exhibit satisficing.
- Trap questions (e.g., “Enter the number 5 in the following text box:”) can identify satisficers and fraudulent survey respondents.

Acquiescence Bias

When presented with agree/disagree, yes/no, or true/false statements, some respondents are more likely to concur with the statement independent of its substance. This tendency is known as acquiescence bias (Smith, 1967).

Respondents are more likely to acquiescence when:

- Cognitive ability is low (Krosnick, Narayan, & Smith, 1996) or motivation is low.
- Question difficulty is high (Stone, Gage, & Leavitt, 1957).
- Personality tendencies skew toward agreeableness (Costa & McCrae, 1988; Goldberg, 1990; Saris, Revilla, Krosnick, & Shaeffer, 2010).
- Social conventions suggest that a “yes” response is most polite (Saris et al., 2010).
- The respondent satisfices and only thinks of reasons why the statement is true, rather than expending cognitive effort to consider reasons for disagreement (Krosnick, 1991).
- Respondents with lower self-perceived status assume that the survey administrator agrees with the posed statement, resulting in deferential agreement bias (Saris et al., 2010).

To minimize acquiescence bias, the following may be considered:

- Avoid questions with agree/disagree, yes/no, true/false, or similar answer options (Krosnick & Presser, 2010).
- Where possible, ask construct-specific questions (i.e., questions that ask about the underlying construct in a neutral, non-leading way) instead of agreement statements (Saris et al., 2010).
- Use reverse-keyed constructs; i.e., the same construct is asked positively and negatively in the same survey. The raw scores of both responses are then combined to correct for acquiescence bias.

Social Desirability

Social desirability occurs when respondents answer questions in a manner they feel will be positively perceived by others (Goffman, 1959; Schlenker & Weigold, 1989). Favorable actions may be overreported, and unfavorable actions or views may be underreported. Topics that are especially prone to social desirability bias include voting behavior, religious beliefs, sexual activity, patriotism, bigotry, intellectual capabilities, illegal acts, acts of violence, and charitable acts.

Respondents are inclined to provide socially desirable answers when:

- Their behavior or views go against the social norm (Holbrook & Krosnick, 2010).
- Asked to provide information on sensitive topics, making the respondent feel uncomfortable or embarrassed about expressing their actual views (Holbrook & Krosnick, 2010).
- They perceive a threat of disclosure or consequences to answering truthfully (Tourangeau, Rips, & Rasinski, 2000).
- Their true identity (e.g., name, address, phone number) is captured in the survey (Paulhus, 1984).
- The data is directly collected by another person (e.g., in-person or phone surveys).

To minimize social desirability bias, respondents should be allowed to answer anonymously or the survey should be self-administered (Holbrook & Krosnick, 2010; Tourangeau & Smith, 1996; Tourangeau & Yan, 2007).

Response Order Bias

Response order bias is the tendency to select the items toward the beginning (i.e., primacy effect) or the end (i.e., recency effect) of an answer list or scale (Chan, 1991; Krosnick & Alwin, 1987; Payne, 1971). Respondents unconsciously interpret the ordering of listed answer options and assume that items near each other are related, top or left items are interpreted to be "first," and middle answers in a scale without a natural order represent the typical value (Tourangeau et al., 2004). Primacy and recency effects are the strongest when the list of answer options is long (Schuman & Presser, 1981) or when they cannot be viewed as a whole (Couper et al., 2004).

To minimize response order effects, the following may be considered:

- Unrelated answer options should be randomly ordered across respondents (Krosnick & Presser, 2010).
- Rating scales should be ordered from negative to positive, with the most negative item first.
- The order of ordinal scales should be reversed randomly between respondents, and the raw scores of both scale versions should be averaged using the same value for each scale label. That way, the response order effects cancel each other out across respondents (e.g., Villar & Krosnick, 2011), unfortunately, at the cost of increasing variability.

Question Order Bias

Order effects also apply to the order of the questions in surveys. Each question in a survey has the potential to bias each subsequent question by priming respondents (Kinder & Iyengar, 1987; Landon, 1971).

The following guidelines may be considered:

- Questions should be ordered from broad to more specific (i.e., a funnel approach) to ensure that the survey follows conversational conventions.
- Early questions should be easy to answer and directly related to the survey topic (to help build rapport and engage respondents) (Dillman, 1978).
- Non-critical, complex, and sensitive questions should be included toward the end of the survey to avoid early drop-off and to ensure collection of critical data.
- Related questions need to be grouped to reduce context switching so that respondents can more easily and quickly access related information from memory, as opposed to disparate items.
- The questionnaire should be divided into multiple pages with distinct sections labeled for easier cognitive processing.

Other Types of Questions to Avoid

Beyond the five common questionnaire biases mentioned above, there are additional question types that can result in unreliable and invalid survey data. These include broad, leading, double-barreled, recall, prediction, hypothetical, and prioritization questions.

Broad questions lack focus and include items that are not clearly defined or those that can be interpreted in multiple ways. For example, “Describe the way you use your tablet computer” is too broad, as there are many aspects to using a tablet such as the purpose, applications being used, and its locations of use. Instead of relying on the respondent to decide on which aspects to report, the research goal as well as core construct(s) should be determined beforehand and asked about in a focused manner. A more focused set of questions for the example above could be “Which apps did you use on your tablet computer over the last week?” and “Describe the locations in which you used your tablet computer last week?”.

Leading questions manipulate respondents into giving a certain answer by providing biasing content or suggesting information the researcher is looking to have confirmed. For example, “This application was recently ranked as number one in customer satisfaction. How satisfied are you with your experience today?”. Another way that questions can lead the respondent toward a certain answer includes those that ask the respondent to agree or disagree with a given statement, as for example in “Do you agree or disagree with the following statement: I use my smartphone more often than my tablet computer.” Note that such questions can additionally result in acquiescence bias (as discussed above). To minimize the effects of leading questions, questions should be asked in a fully neutral way without any examples or additional information that may bias respondents toward a particular response.

Double-barreled questions ask about multiple items while only allowing for a single response, resulting in less reliable and valid data. Such questions can usually be detected by the existence of the word “and.” For example, when asked “How satisfied or dissatisfied are you with your smartphone and tablet computer?”, a respondent with differing attitudes toward the two devices will be forced to pick an attitude that either reflects just one device or the average across both devices. Questions with multiple items should be broken down into one question per construct or item.

Recall questions require the respondent to remember past attitudes and behaviors, leading to recall bias (Krosnick & Presser, 2010) and inaccurate recollections. When a respondent is asked “How many times did you use an Internet search engine over the past 6 months?”, they will try to rationalize a plausible number, because recalling a precise count is difficult or impossible. Similarly, asking questions that compare past attitudes to current attitudes, as in “Do you prefer the previous or current version of the interface?”, may result in skewed data due to difficulty remembering past attitudes. Instead, questions should focus on the present, as in “How satisfied or dissatisfied are you with your smartphone today?”, or use a recent time frame, for example, “In the past hour, how many times did you use an Internet search engine?”. If the research goal is to compare attitudes or behaviors across different product versions or over time, the researcher should field separate surveys for each product version or time period and make the comparison themselves.

Prediction questions ask survey respondents to anticipate future behavior or attitudes, resulting in biased and inaccurate responses. Such questions include “Over the next month, how frequently will you use an Internet search engine?”. Even more cognitively burdensome are *hypothetical* questions, i.e., asking the respondent to imagine a certain situation in the future and then predicting their attitude or behavior in that situation. For example, “Would you purchase more groceries if the store played your favorite music?” and “How much would you like this Website if it used blue instead of red for their color scheme?” are hypothetical questions. Other frequently used hypothetical questions are those that ask the respondent to prioritize a future feature set, as in “Which of the following features would make you more satisfied with this product?”. Even though the respondent may have a clear answer to this question, their response does not predict actual future usage of or satisfaction with the product if that feature was added. Such questions should be entirely excluded from surveys.

Leveraging Established Questionnaires

An alternative to constructing a brand new questionnaire is utilizing questionnaires developed by others. These usually benefit from prior validation and allow researchers to compare results with other studies that used the same questionnaire. When selecting an existing questionnaire, one should consider their particular research goals and study needs and adapt the questionnaire as appropriate. Below are commonly used HCI-related questionnaire instruments. Note that as survey research methodology has significantly advanced over time, each questionnaire should be assessed for potential sources of measurement error, such as the biases and the to-be-avoided question types mentioned previously.

- *NASA Task Load Index (NASA TLX)*. Originally developed for aircraft cockpits, this questionnaire allows researchers to subjectively assess the workload of operators working with human–machine systems. It measures mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart & Staveland, 1988).
- *Questionnaire for User Interface Satisfaction (QUIS)*. This questionnaire assesses one's overall reaction to a system, including its software, screen, terminology, system information, and learnability (Chin, Diehl, & Norman, 1988).
- *Software Usability Measurement Inventory (SUMI)*. This questionnaire measures perceived software quality covering dimensions such as efficiency, affect, helpfulness, control, and learnability, which are then summarized into a single satisfaction score (Kirakowski & Corbett, 1993).
- *Computer System Usability Questionnaires (CSUQ)*. This questionnaire developed by IBM measures user satisfaction with system usability (Lewis, 1995).
- *System Usability Scale (SUS)*. As one of the most frequently used scales in user experience, SUS measures attitudes regarding the effectiveness, efficiency, and satisfaction with a system with ten questions, yielding a single score (Brooke, 1996).
- *Visual Aesthetics of Website Inventory (VisAwi)*. This survey measures perceived visual aesthetics of a Website on the four subscales of simplicity, diversity, colorfulness, and craftsmanship (Moshagen & Thielsch, 2010).

Visual Survey Design Considerations

Researchers should also take into account their survey's visual design, since specific choices, including the use of images, spacing, and progress bars, may unintentionally bias respondents. This section summarizes such visual design aspects; for more details, refer to Couper (2008).

While objective images (e.g., product screenshots) can help clarify questions, context-shaping images can influence a respondent's mindset. For example, when asking respondents to rate their level of health, presenting an image of someone in a hospital bed has a framing effect that results in higher health ratings compared to that of someone jogging (Couper, Conrad, & Tourangeau, 2007).

The visual treatment of response options also matters. When asking closed-ended questions, uneven spacing between horizontal scale options results in a higher selection rate for scale points with greater spacing; evenly spaced scale options are recommended (Tourangeau, Couper, & Conrad, 2004). Drop-down lists, compared to radio buttons, have been shown to be harder and slower to use and to result in more accidental selections (Couper, 2011). Lastly, larger text fields increase the amount of text entered (Couper, 2011) but may intimidate respondents, potentially causing higher break-offs (i.e., drop-out rates).

Survey questions can be presented one per page, multiple per page, or all on one page. Research into pagination effects on completion rates is inconclusive (Couper, 2011). However, questions appearing on the same page may have higher correlations with each other, a sign of measurement bias (Peytchev, Couper, McCabe, & Crawford, 2006). In practice, most Internet surveys with skip logic use multiple pages, whereas very short questionnaires are often presented on a single page.

While progress bars are generally preferred by respondents and are helpful for short surveys, their use in long surveys or surveys with skip logic can be misleading and intimidating. Progress between pages in long surveys may be small, resulting in increased break-off rates (Callegaro, Villar, & Yang, 2011). On the other hand, progress bars are likely to increase completion rates for short surveys, where substantial progress is shown between pages.

Review and Survey Pretesting

At this point in the survey life cycle, it is appropriate to have potential respondents take and evaluate the survey in order to identify any remaining points of confusion. For example, the phrase "mobile device" may be assumed to include mobile phones, tablets, and in-car devices by the researcher, while survey respondents may interpret it to be mobile phones only. Or, when asking for communication tools used by the respondent, the provided list of answer choices may not actually include all possible options needed to properly answer the question. Two established evaluation methods used to improve survey quality are cognitive pretesting and field testing the survey by launching it to a subset of the actual sample, as described more fully in the remainder of this section. By evaluating surveys early on, the researcher can identify disconnects between their own assumptions and how respondents will read, interpret, and answer questions.

Cognitive Pretesting

To conduct a cognitive pretest, a small set of potential respondents is invited to participate in an in-person interview where they are asked to take the survey while using the think-aloud protocol (similar to a usability study). A cognitive pretest assesses question interpretation, construct validity, and comprehension of survey terminology and calls attention to missing answer options or entire questions (Bolton & Bronkhorst, 1995; Collins, 2003; Drennan, 2003; Presser et al., 2004). However, note that due to the testing environment, a cognitive pretest does not allow the researcher to understand contextual influences that may result in break-off or not filling out the survey in the first place.

As part of a pretest, participants are asked the following for each question:

1. "Read the entire question and describe it in your own words."
2. "Select or write an answer while explaining your thought process."
3. "Describe any confusing terminology or missing answer choices."

During the interview, the researcher should observe participant reactions; identify misinterpretations of terms, questions, answer choices, or scale items; and gain insight into how respondents process questions and come up with their answers. The researcher then needs to analyze the collected information to improve problematic areas before fielding the final questionnaire. A questionnaire could go through several rounds of iteration before reaching the desired quality.

Field Testing

Piloting the survey with a small subset of the sample will help provide insights that cognitive pretests alone cannot (Collins, 2003; Presser et al., 2004). Through field testing, the researcher can assess the success of the sampling approach, look for common break-off points and long completion times, and examine answers to open-ended questions. High break-off rates and completion times may point to flaws in the survey design (see the following section), while unusual answers may suggest a disconnect between a question's intention and respondents' interpretation. To yield additional insights from the field test, a question can be added at the end of each page or at the end of the entire survey where respondents can provide explicit feedback on any points of confusion. Similar to cognitive pretests, field testing may lead to several rounds of questionnaire improvement as well as changes to the sampling method. Finally, once all concerns are addressed, the survey is ready to be fielded to the entire sample.

Implementation and Launch

When all questions are finalized, the survey is ready to be fielded based on the chosen sampling method. Respondents may be invited through e-mails to specifically named persons (e.g., respondents chosen from a panel), intercept pop-up dialogs while using a product or a site, or links placed directly in an application (see the sampling section for more details; Couper, 2000).

There are many platforms and tools that can be used to implement Internet surveys, such as ConfirmIt, Google Forms, Kinesis, LimeSurvey, SurveyGizmo, SurveyMonkey, UserZoom, Wufoo, and Zoomerang, to name just a few. When deciding on the appropriate platform, functionality, cost, and ease of use should be taken into consideration. The questionnaire may require a survey tool that supports functionality such as branching and conditionals, the ability to pass URL parameters, multiple languages, and a range of question types. Additionally, the researcher may want to customize the visual style of the survey or set up an automatic reporting dashboard, both of which may only be available on more sophisticated platforms.

Piping Behavioral Data into Surveys

Some platforms support the ability to combine survey responses with other log data, which is referred to as piping. Self-reported behaviors, such as frequency of use, feature usage, tenure, and platform usage, are less valid and reliable compared to generating the same metrics through log data. By merging survey responses with behavioral data, the researcher can more accurately understand the relationship between respondent characteristics and their behaviors or attitudes. For example, the researcher may find that certain types of users or the level of usage may correlate with higher reported satisfaction. Behavioral data can either be passed to the results database as a parameter in the survey invitation link or combined later via a unique identifier for each respondent.

Monitoring Survey Paradata

With the survey's launch, researchers should monitor the initial responses as well as survey paradata to identify potential mistakes in the survey design. Survey paradata is data collected about the survey response process, such as the devices from which the survey was accessed, time to survey completion, and various response-related rates. By monitoring such metrics, the survey researcher can quickly apply improvements before the entire sample has responded to the survey. The American Association for Public Opinion Research specified a set of definitions for commonly used paradata metrics (AAPOR, 2011):

- Click-through rate: Of those invited, how many opened the survey.
- Completion rate: Of those who opened the survey, how many finished the survey.
- Response rate: Of those invited, how many finished the survey.
- Break-off rate: Of those who started, how many dropped off on each page.
- Completion time: The time it took respondents to finish the entire survey.

Response rates are dependent on a variety of factors, the combination of which makes it difficult to specify an acceptable response rate in HCI survey research. A meta-analysis of 31 e-mail surveys from 1986 to 2000 showed that average response rates for e-mail surveys typically fall between 30 and 40 %, with follow-up reminders significantly increasing response rates (Sheehan, 2001). Another review of 69 e-mail surveys showed that response rates averaged around 40 % (Cook, Heath, & Thompson, 2000). When inviting respondents through Internet intercept surveys (e.g., pop-up surveys or in-product links), response rates may be 15 % or lower (Couper, 2000). Meta-analyses of mailed surveys showed that their response rates are 40–50 % (Kerlinger, 1986) or 55 % (Baruch, 1999). In experimental comparisons to mailed surveys, response rates to Internet e-mail surveys were about 10 % lower (Kaplowitz, Hadlock, & Levine, 2004; Manfreda et al., 2008). Such meta reviews also showed that overall response rates have been declining over several decades (Baruch, 1999; Baruch & Holtom, 2008; Sheehan, 2001); however, this decline seems to have stagnated around 1995 (Baruch & Holtom, 2008).

Maximizing Response Rates

In order to gather enough responses to represent the target population with the desired level of precision, response rates should be maximized. Several factors affect response rates, including the respondents' interest in the subject matter, the perceived impact of responding to the survey, questionnaire length and difficulty, the presence and nature of incentives, and researchers' efforts to encourage response (Fan & Yan, 2010).

Based on experimentation with invitation processes for mail surveys, Dillman (1978) developed the "Total Design Method" to optimize response rates. This method, consistently achieving response rates averaging 70 % or better, consists of a timed sequence of four mailings: the initial request with the survey on week one, a reminder postcard on week two, a replacement survey to non-respondents on week four, and a second replacement survey to non-respondents by certified mail on week seven. Dillman incorporates social exchange theory into the Total Design Method by personalizing the invitation letters, using official stationery to increase trust in the survey's sponsorship, explaining the usefulness of the survey research and the importance of responding, assuring the confidentiality of respondents' data, and beginning the questionnaire with items directly related to the topic of the survey (1991). Recognizing the need to cover Internet and mixed-mode surveys, Dillman extended his prior work with the "Tailored Design Method." With this update, he emphasized customizing processes and designs to fit each survey's topic, population, and sponsorship (2007).

Another component of optimizing response rates is getting as many complete responses as possible from those who start the survey. According to Peytchev (2009), causes of break-off may fall into the following three categories:

- Respondent factors (survey topic salience and cognitive ability)
- Survey design factors (length, progress indicators, and incentives)
- Question design factors (fatigue and intimidation from open-ended questions and lengthy grid questions)

The questionnaire design principles mentioned previously may help minimize break-off, such as making surveys as short as possible, having a minimum of required questions, using skip logic, and including progress bars for short surveys.

Providing an incentive to encourage survey responses may be advantageous in certain cases. Monetary incentives tend to increase response rates more than non-monetary incentives (Singer, 2002). In particular, non-contingent incentives, which are offered to all people in the sample, generally outperform contingent incentives, given only upon completion of the survey (Church, 1993). This is true even when a non-contingent incentive is considerably smaller than a contingent incentive. One strategy to maximize the benefit of incentives is to offer a small non-contingent award to all invitees, followed by a larger contingent award to initial non-respondents (Lavrakas, 2011). An alternate form of contingent incentive is a lottery, where a drawing is held among respondents for a small number of monetary awards or other prizes. However, the efficacy of such lotteries is unclear (Stevenson, Dykema, Cyffka, Klein, & Goldrick-Rab, 2012). Although incentives will typically increase response rates, it is much less certain whether they increase the representativeness of the results. Incentives are likely most valuable when facing a small population or sampling frame, and high response rates are required for sufficiently precise measurements. Another case where incentives may help is when some groups in the sample have low interest in the survey topic (Singer, 2002). Furthermore, when there is a cost to contact each potential respondent, as with door-to-door interviewing, incentives will decrease costs by lowering the number of people that need to be contacted.

Data Analysis and Reporting

Once all the necessary survey responses have been collected, it is time to start making sense of the data by:

1. Preparing and exploring the data
2. Thoroughly analyzing the data
3. Synthesizing insights for the target audience of this research

Data Preparation and Cleaning

Cleaning and preparing survey data before conducting a thorough analysis are essential to identify low-quality responses that may otherwise skew the results. When taking a pass through the data, survey researchers should look for signs of poor-quality responses. Such survey data can either be left as is, removed, or presented separately from trusted data. If the researcher decides to remove poor data, they must cautiously decide whether to remove data on the respondent level (i.e., listwise deletion), an individual question level (i.e., pairwise deletion), or only beyond a certain point in the survey where respondents' data quality is declined. The following are signals that survey researchers should look out for at the survey response level:

- *Duplicate responses*. In a self-administered survey, a respondent might be able to fill out the survey more than once. If possible, respondent information such as name, e-mail address, or any other unique identifier should be used to remove duplicate responses.
- *Speeders*. Respondents that complete the survey faster than possible, speeders, may have carelessly read and answered the questions, resulting in arbitrary responses. The researcher should examine the distribution of response times and remove any respondents that are suspiciously fast.
- *Straight-liners and other questionable patterns*. Respondents that always, or almost always, pick the same answer option across survey questions are referred to as straight-liners. Grid-style questions are particularly prone to respondent straight-lining (e.g., by always picking the first answer option when asked to rate a series of objects). Respondents may also try to hide the fact that they are randomly choosing responses by answering in a fixed pattern (e.g., by alternating between the first and second answer options across questions). If a respondent straight-lines through the entire survey, the researcher may decide to remove the respondent's data entirely. If a respondent starts straight-lining at a certain point, the researcher may keep data up until that point.
- *Missing data and break-offs*. Some respondents may finish a survey but skip several questions. Others may start the survey but break off at some point. Both result in missing data. It should first be determined whether those who did not respond to certain questions are different from those who did. A non-response study should be conducted to assess the amount of non-response bias for each survey question. If those who did not answer certain questions are not meaningfully different from those who did, the researcher can consider leaving the data as is; however, if there is a difference, the researcher may choose to impute plausible values based on similar respondents' answers (De Leeuw, Hox, & Huisman, 2003).

Furthermore, the following signals may need to be assessed at a question-by-question level:

- *Low inter-item reliability*. When multiple questions are used to measure a single construct, respondents' answers to these questions should be associated with each other. Respondents that give inconsistent or unreliable responses (e.g., selecting "very fast" and "very slow" for separate questions assessing the construct of speed) may not have carefully read the set of questions and should be considered for removal.
- *Outliers*. Answers that significantly deviate from the majority of responses are considered outliers and should be examined. For questions with numeric values, some consider outliers as the top and bottom 2 % of responses, while others calculate outliers as anything outside of two or three standard deviations from the mean. Survey researchers should determine how much of a difference keeping or removing the outliers has on variables' averages. If the impact is significant, the researcher may either remove such responses entirely or replace them with a value that equals two or three standard deviations from the mean. Another way to describe the central tendency while minimizing the effect of outliers is to use the median, rather than the mean.

- *Inadequate open-ended responses*. Due to the amount of effort required, open-ended questions may lead to low-quality responses. Obvious garbage and irrelevant answers, such as “asdf,” should be removed, and other answers from the same respondent should be examined to determine whether all their survey responses warrant removal.

Analysis of Closed-Ended Responses

To get an overview of what the survey data shows, *descriptive statistics* are fundamental. By looking at measures such as the frequency distribution, central tendency (e.g., mean or median), and data dispersion (e.g., standard deviation), emerging patterns can be uncovered. The frequency distribution shows the proportion of responses for each answer option. The central tendency measures the “central” position of a frequency distribution and is calculated using the mean, median, and mode. Dispersion examines the data spread around the central position through calculations such as standard deviation, variance, range, and interquartile range.

While descriptive statistics only describe the existing data set, *inferential statistics* can be used to draw inferences from the sample to the overall population in question. Inferential statistics consists of two areas: estimation statistics and hypothesis testing. Estimation statistics involves using the survey’s sample in order to approximate the population’s value. Either the margin of error or the confidence interval of the sample’s data needs to be determined for such estimation. To calculate the margin of error for an answer option’s proportion, only the sample size, the proportion, and a selected confidence level are needed. However, to determine the confidence interval for a mean, the standard error of the mean is required additionally. A confidence interval thus represents the estimated range of a population’s mean at a certain confidence level.

Hypothesis testing determines the probability of a hypothesis being true when comparing groups (e.g., means or proportions being the same or different) through the use of methods such as *t*-test, ANOVA, or Chi-square. The appropriate test is determined by the research question, type of prediction by the researcher, and type of variable (i.e., nominal, ordinal, interval, or ratio). An experienced quantitative researcher or statistician should be involved.

Inferential statistics can also be applied to identify connections among variables:

- *Bivariate correlations* are widely used to assess linear relationships between variables. For example, correlations can indicate which product dimensions (e.g., ease of use, speed, features) are most strongly associated with users’ overall satisfaction.
- *Linear regression* analysis indicates the proportion of variance in a continuous dependent variable that is explained by one or more independent variables and the amount of change explained by each unit of an independent variable.

- *Logistic regression* predicts the change in probability of getting a particular value in a binary variable, given a unit change in one or more independent variables.
- *Decision trees* assess the probabilities of reaching specific outcomes, considering relationships between variables.
- *Factor analysis* identifies groups of covariates and can be useful to reduce a large number of variables into a smaller set.
- *Cluster analysis* looks for related groups of respondents and is often used by market researchers to identify and categorize segments within a population.

There are many packages available to assist with survey analysis. Software such as Microsoft Excel, and even certain survey platforms such as SurveyMonkey or Google Forms, can be used for basic descriptive statistics and charts. More advanced packages such as SPSS, R, SAS, or Matlab can be used for complex modeling, calculations, and charting. Note that data cleaning often needs to be a precursor to conducting analysis using such tools.

Analysis of Open-Ended Comments

In addition to analyzing closed-ended responses, the review of open-ended comments contributes a more holistic understanding of the phenomena being studied. Analyzing a large set of open-ended comments may seem like a daunting task at first; however, if done correctly, it reveals important insights that cannot otherwise be extracted from closed-ended responses. The analysis of open-ended survey responses can be derived from the method of *grounded theory* (Böhm, 2004; Glaser & Strauss, 1967) (see chapter on “Grounded Theory Methods”).

An interpretive method, referred to as *coding* (Saldaña, 2009), is used to organize and transform qualitative data from open-ended questions to enable further quantitative analysis (e.g., preparing a frequency distribution of the codes or comparing the responses across groups). The core of such qualitative analysis is to assign one or several codes to each comment; each code consists of a word or a short phrase summarizing the essence of the response with regard to the objective of that survey question (e.g., described frustrations, behavior, sentiment, or user type). Available codes are chosen from a coding scheme, which may already be established by the community or from previous research or may need to be created by the researchers themselves. In most cases, as questions are customized to each individual survey, the researcher needs to establish the coding system using a deductive or an inductive approach.

When employing a *deductive* approach, the researcher defines the full list of possible codes in a top-down fashion; i.e., all codes are defined before reviewing the qualitative data and assigning those codes to comments. On the other hand, when using an *inductive* approach to coding, the codes are generated and constantly revised in a bottom-up approach; i.e., the data is coded according to categories identified by reading and re-reading responses to the open-ended question. Bottom-up, inductive coding is recommended, as it has the benefit of capturing categories the researcher may not have thought of before reading the actual comments; however, it requires more coordination if multiple coders are involved. (See "Grounded Theory Method" chapter for an analogous discussion.)

To measure the reliability of both the developed coding system and the coding of the comments, either the same coder should partially repeat the coding or a second coder should be involved. *Intra-rater reliability* describes the degree of agreement when the data set is reanalyzed by the same researcher. *Inter-rater reliability* (Armstrong, Gosling, Weinman, & Marteau, 1997; Gwet, 2001) determines the agreement level of the coding results from at least two independent researchers (using correlations or Cohen's kappa). If there is low agreement, the coding needs to be reviewed to identify the pattern behind the disagreement, coder training needs to be adjusted, or changes to codes need to be agreed upon to achieve consistent categorization. If the data set to be coded is too large and coding needs to be split up between researchers, inter-rater consistency can be measured by comparing results from coding an overlapping set of comments, by comparing the coding to a preestablished standard, or by including another researcher to review overlapping codes from the main coders.

After having analyzed all comments, the researcher may prepare descriptive statistics such as a frequency distribution of codes, conduct inferential statistical tests, summarize key themes, prepare necessary charts, and highlight specifics through the use of representative quotes. To compare results across groups, inferential analysis methods can be used as described above for closed-ended data (e.g., *t*-tests, ANOVA, or Chi-square).

Assessing Representativeness

A key criterion in any survey's quality is the degree to which the results accurately represent the target population. If a survey's sampling frame fully covers the population and the sample is randomly drawn from the sampling frame, a response rate of 100 % would ensure that the results are representative at a level of precision based on the sample size.

If, however, a survey has less than a 100 % response rate, those not responding might have provided a different answer distribution than those who did respond.

An example is a survey intended to measure attitudes and behaviors regarding a technology that became available recently. Since people who are early adopters of new technologies are usually very passionate about providing their thoughts and feedback, surveying users of this technology product would overestimate responses from early adopters (as compared to more occasional users) and the incidence of favorable attitudes toward that product. Thus, even a modest level of non-response can greatly affect the degree of non-response bias.

With response rates to major longitudinal surveys having decreased over time, much effort has been devoted to understanding non-response and its impact on data quality as well as methods of adjusting results to mitigate non-response error. Traditional survey assumptions held that maximizing response rates minimized non-response bias (Groves, 2006). Therefore, the results of Groves' 2006 meta-analysis were both surprising and seminal, finding no meaningful correlation between response rates and non-response error across mail, telephone, and face-to-face surveys.

Reporting Survey Findings

Once the question-by-question analysis is completed, the researcher needs to synthesize findings across all questions to address the goals of the survey. Larger themes may be identified, and the initially defined research questions are answered, which are in turn translated into recommendations and broader HCI implications as appropriate. All calculations used for the data analysis should be reported with the necessary statistical rigor (e.g., sample sizes, *p*-values, margins of error, and confidence levels). Furthermore, it is important to list the survey's paradata and include response and break-off rates (see section on monitoring survey paradata).

Similar to other empirical research, it is important to not only report the results of the survey but also describe the original research goals and the used survey methodology. A detailed description of the survey methodology will explain the population being studied, sampling method, survey mode, survey invitation, fielding process, and response paradata. It should also include screenshots of the actual survey questions and explain techniques used to evaluate data quality. Furthermore, it is often necessary to include a discussion on how the respondents compare to the overall population. Lastly, any potential sources of survey bias, such as sampling biases or non-response bias, should be outlined.

Exercises

1. What are the differences between a survey and a questionnaire, both in concept and design?
2. In your own research area, create a survey and test it with five classmates. How long do you think it will take a classmate to fill it out? How long did it take them?

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