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PRACTICAL APPLICATION

An Overview of Data Collection in Health Preference Research

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Abstract
This paper focuses on survey administration and data collection methods employed for stated-preference studies in health applications. First, it describes different types of survey administration methods, encompassing web-based surveys, face-to-face (in-person) surveys, and mail surveys. Second, the concept of sampling frames is introduced, clarifying distinctions between the target population and survey frame population. The discussion then extends to different types of sampling methods, such as probability and non-probability sampling, along with an evaluation of potential issues associated with different sampling methods within the context of health preference research. Third, the paper provides information about different recruitment methods, including web-surveys, leveraging patient groups, and in-clinic recruitment. Fourth, a crucial aspect addressed is the calculation of response rate, with insights into determining an adequate response rate and strategies to improve response rates in stated-preference surveys. Lastly, the paper concludes by discussing data management plans and suggesting insights for future research in this field. In summary, this paper examines the nuanced aspects of survey administration and data collection methods in stated-preference studies, offering valuable guidance for researchers and practitioners in the health domain.

Key Points for Decision Makers

The paper comprehensively examines survey administration and data collection methods in stated-preference studies within health applications, covering various survey administration methods, sampling frames, sampling methods, recruitment strategies, and response rate calculations.

It provides valuable guidance for researchers and practitioners in the health domain, addressing nuanced aspects of survey methodology and offering insights into data management plans, concluding with suggestions for future research in the field of stated-preference studies.

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1 Introduction

This paper serves as a guide to the survey administration and data collection process in health preference research, particularly aimed at researchers new to the field. While newcomers to primary data collection can refer to existing literature for insights into survey administration and data collection methods across various disciplines [1–4], this paper aims to elucidate the specific considerations inherent to stated preference studies within health applications. The paper starts by describing commonly employed modes of survey administration. It then delves into the challenges in designing a sampling frame and explores various sampling techniques that can be used. Following this, the paper outlines the common approaches used to recruit survey respondents and addresses concerns related to defining and improving response rates. The paper also introduces data management practices before concluding with a summary of the present state of data collection and potential avenues for future research in this area.

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2 Survey Administration Modes

There are a variety of different survey administration methods that can be used to elicit preferences for health goods and services. This section reviews three primary methods: mail surveys, face-to-face (or in person) surveys, and web-based surveys. We will outline the advantages and disadvantages associated with each method, considering factors, such as cost, speed, and generalizability. It is worth noting that the choice of the most suitable survey administration method may also depend on specific characteristics of the target sample, such as cognitive burden (e.g., elderly population), location (rural versus urban settings), or disease context (e.g., rare versus common diseases). Table 1 provides a summary of the different methods of survey administration.

2.1 Mail Survey

Paper-based mail surveys involve the dissemination of physical paper questionnaires to respondents through the postal service, with respondents returning the completed questionnaires through the same mail service. The main advantage of this method lies in its ease of implementation once a database of addresses is available [5]. Although the response rates to mail surveys have declined over the years [6], there is still evidence showing that they may yield higher response rates than web surveys [7, 8]. In addition, using postal addresses can facilitate reaching a national representative sample when targeting the general population [9]. However, acquiring the addresses of potential respondents and waiting for their responses can be time-consuming and logistically challenging [9]. Another drawback is the requirement for double data entry, as the information from the paper forms must be manually entered into a digital format for analysis, aiming to avoid data entry errors [10].

2.2 Face-to-Face (in Person) Survey

Face-to-face or in-person surveys involve interviewers personally interacting with respondents using paper-forms, computers, tablets, or phones/personal digital assistants (PDAs). There are three main types of in-person surveys: (1) interviewer-administered, where the enumerator administers the survey to the respondent; (2) interviewer-assisted, where the enumerator assists if the respondent needs help; and (3) self-administered, where the enumerator provides the survey to the respondent on paper or computer, allowing them to complete it independently [11, 12].

Table 1 Survey administration modes

Mode	Advantages	Disadvantages
Mail survey: Respondents receive physical paper questionnaires through the postal service, and they return the completed questionnaires via the same mail service	• Easy to implement once a database of addresses is available • Yields higher response rates than web surveys • Can facilitate reaching a national representative sample when targeting the general population	• Acquiring the addresses of potential respondents can be difficult and time-consuming • Waiting for their responses can take time • Double-entry of data is required
Face-to-face survey: Interviewers personally interact with respondents. They can be interviewer-administered, interviewer-assisted, or self-administered	• Control over survey implementation • Interviewers can address any issues promptly • Interviewers can clarify or translate complex or unclear survey questions and choice tasks	• Time-consuming • Costly • Potential for social desirability or other biases
Web-based survey: Respondents complete the survey by clicking on a link sent to them on their computer, phone, or tablet	• Automatic data entry • Easy implementation of skip logic • Rapid data collection • Reaching a broader geographical area • Flexibility for completing at respondents' preferred time and location • Ease of programming complex randomization	• Sampling bias (higher income, younger, and more educated respondents) • Requires access to internet and device • Potential environmental distractions • Potential for fraudulent or fabricated data • Requires digital literacy

The main advantage of this method is the level of control researchers have over the survey context, ensuring participant focus and comprehension [13]. Unlike online or mail surveys, where it is challenging to gauge participant engagement, face-to-face surveys allow researchers to directly observe respondents and promptly address any emergent issues [14]. Researchers can conduct interviews themselves or debrief with interviewers, facilitating the swift identification of issues with the survey or preference task [15]. In cases where tasks are complex, interviewers can clarify complex attributes and levels, and check participant rationality using methods like the think-aloud protocol, which has shown promise in reducing hypothetical bias in stated preference surveys [16, 17]. Furthermore, face-to-face surveys allow participants to ask interviewers for further explanation of difficult tasks, providing an opportunity to clarify important aspects of choice tasks or specific attributes [15]. Finally, if the survey is in a language that is not the mother tongue of participants, bilingual interviewers can offer on-the-spot translation to enhance understanding [18]. Nonetheless, this may require addressing potential variation during data analysis to ensure comparability across interviewers [19].

However, face-to-face surveys have some drawbacks, primarily related to time and cost [20, 21]. Achieving a representative sample from a physical sampling frame can be time-consuming, and recruiting and retaining qualified interviewers, as well as transporting them to survey locations, may result in high expenses [22]. In addition, the presence of an interviewer may introduce social desirability or other biases associated with face-to-face interactions [23, 24]. This is particularly relevant in surveys covering sensitive topics, such as addictive behaviors, sexual health, or conditions with potentially embarrassing side effects or treatments [25–27].

2.3 Web-Based Survey

Web-based surveys have emerged as a convenient method for conducting health preference surveys. Researchers can utilize survey-hosting platforms, such as Survey Monkey or Qualtrics, to create user-friendly websites that administer the survey, including stated-preference questions. Participants typically receive a link to the survey via e-mail or regular mail, and can complete it on a range of devices, such as computers, tablets, or smartphones [28]. However, it is crucial that surveys be designed to ensure compatibility across different devices, especially when choice tasks involve images. In a study investigating access devices for web surveys in preference studies, findings revealed no significant differences in failure rates of dominance checks, "flat-lining" (always choosing alternative A or alternative B), respondent-reported attribute non-attendance, and respondent-rated task difficulty based on device choice [28]. However, respondents using desktop or laptop personal computers tended to complete surveys more quickly and were less likely to speed through survey webpages compared with those using handheld devices.

Web-based surveys offer several advantages over other methods. First, participant data are automatically saved in databases, eliminating the need for manual data entry [29]. This can mean web-based surveys incur lower costs than other alternative methods [8, 30] and avoid potential errors during data entry [31]. Second, skip logic, bypassing irrelevant questions for respondents on the basis of prior responses [32], can be easily implemented, reducing coding errors, respondent burden, and instances of missing data [33]. Third, data collection can be potentially faster compared with mail and face-to-face surveys [34]. Fourth, web surveys enable researchers to reach a broader geographical area, including individuals from rural or distant locations through mitigation of the need to travel [35]. Fifth, respondents benefit from the convenience of completing the survey at their preferred time and location and having time to think through their responses [35]. Last, a major advantage of web-based surveys, particularly for stated-preference surveys, is the possibility for complex randomization of attributes, alternatives, and tasks [36]. Choice tasks in surveys, such as discrete choice experiments (DCEs), typically have multiple versions distributed across blocks, and randomizing each person to a block can be efficiently achieved through web-based platforms. In addition, researchers concerned about potential fatigue or learning effects [36] can easily and reliably randomize the order of choice tasks [37].

Despite these advantages, web-based surveys have drawbacks. One significant concern is their reliance on participants having access to reliable internet, a smartphone or device, and a stable electricity supply. Unfortunately, these requirements may not always be met, especially among individuals with lower income and those in low- or middle-income countries [38, 39]. In addition, web surveys may pose challenges for individuals with poor digital literacy, such as older individuals. Such individuals may be less likely to participate in a study and may struggle with interpreting information, completing choice tasks, and navigating the web survey interface [35]. Therefore, participants in web surveys tend to be younger and have higher incomes and education levels [15, 40–42], potentially skewing the results. However, as internet coverage expands and technology becomes more accessible and affordable, reaching diverse populations will become easier, particularly in high-income countries.

Another drawback worth noting is the presence of potential distractions, such as family members, phones, or the option to leave the survey, which can affect participants' focus [43, 44]. Similarly, web surveys lack control over who completes

them, making them vulnerable to fraudulent or fabricated data, a concern that has grown in recent years [45, 46]. This will be discussed further in the recruitment section.

2.4 Comparing Survey Modes in Health Preference Research

There has been a relatively limited number of studies comparing different survey modes in health preference research, and respondent characteristics have varied on the basis of the mode of survey administration [8, 14, 47, 48]. However, the study findings have been mixed. For example, some studies found different preferences and findings when comparing web and face-to-face surveys [14, 15], while others found no significant differences [48]. Similarly, differences in preferences have been observed in some studies comparing web surveys to mail surveys [8], but not in others [47]. When the sampling frame was controlled, findings also varied. For example, one study found that mail surveys produced a higher willingness to pay compared with web surveys in an environmental application [49] while another study found the opposite trend in a health application [33].

Respondents tended to complete web surveys faster compared with other survey modes [8, 33, 48], and web surveys generally had lower rates of missing items compared with mail surveys [47]. However, when compared with face-to-face surveys, web surveys exhibited a greater prevalence of potentially suspicious choice patterns [15]. Given these varied findings, more research is needed before drawing conclusive insights regarding the use of different survey modes in health preference research. However, considering the escalating rate of internet usage and technological advancements, it is reasonable to anticipate that web surveys will increasingly dominate this domain.

3 Sampling Frame

3.1 Target Population versus Frame Population

In health preference research, the concept of the target population is typically well-defined at the beginning of a project. However, identifying the frame population, which represents the group of individuals from which the survey sample will be drawn, can be challenging [50]. For example, if the research focuses on individuals with a specific cancer type, the target population would encompass all individuals affected by that condition. To survey the preferences of this target population, the frame population may be selected from attendees in a hospital oncology unit. However, there are potential problems with this approach.

Using this example, one issue is that not all individuals with the specific cancer may regularly visit a hospital oncology unit. This could include those in the early stages of the disease or those with stable conditions. The significance of this issue depends on a range of factors. For example, it becomes more critical if a large proportion of the target population is not represented in the frame population. It also matters if those outside the frame population are likely to have different preferences compared with those within it. In this section, we will introduce strategies for selecting a sampling frame, discuss different sampling techniques, and outline some of the major problems and biases associated with each approach.

It is important to acknowledge that the target population and frame population rarely perfectly intersect. Therefore, research teams must identify a pragmatic and justifiable approach that minimizes coverage biases. Regardless of the selected frame population, it is essential for researchers to understand how the sample was obtained and recognize that the sampling frame may be an imperfect proxy for the entire target population. This understanding allows researchers to derive statistical estimates reasonably and helps the audience of the research understand the context in which the findings should be interpreted.

3.2 Selecting a Sampling Frame

Selecting an appropriate sampling frame is a challenging task in health preference research and involves striking a balance between various considerations. Defining inclusion and exclusion criteria is valuable to ensure the sampling frame closely aligns with the target population under investigation. However, practical considerations may limit the ability to achieve this. The definition of an appropriate sampling frame is closely aligned with the merits of different sampling techniques, which is discussed in more detail below.

3.3 Types of Sampling

In health preference research, there are two main types of sampling: probability sampling and nonprobability sampling.

3.3.1 Probability Sampling

Probability sampling ensures that every individual in the population has a nonzero chance of being included in the sample [51]. There are several approaches to probability sampling, each with its own advantages and considerations.

Simple random sampling involves randomly selecting individuals from a sampling frame, such as a list of people with a specific condition [52]. It allows each member of the frame population to have an equal likelihood of being selected for the study, minimizing sampling bias. One example might be administering a time trade-off study (which typically requires in person interviews) in a large country such as the USA or Australia with vast geographical spread [53].

Systematic sampling involves selecting individuals on the basis of a prespecified rule, such as every fifth patient in a hospital [54]. It is not widely used in health preference research since it is not statistically superior to simple random sampling. Nevertheless, it can be useful in situations where consecutive sampling may cause delays or inconvenience.

Stratified sampling involves grouping potential respondents on the basis of predetermined characteristics, such as age, sex, or disease severity, and randomly selecting individuals from each group [55, 56]. It helps ensure a sample that closely matches the ideal distribution across these characteristics, which is typically representative of the target population. This approach is valuable when the frame population differs from the target population, addressing issues, such as the overrepresentation of certain groups in web-based surveys.

Cluster random sampling involves dividing the frame population into clusters usually on the basis of geographic or spatial characteristics and randomly selecting a sample of clusters [57, 58]. The sampling will include all individuals in each cluster. This approach is more practical than stratified sampling [51] but also can be used together with stratified sampling [59, 60]. It is useful when it is impractical to recruit respondents from the entire frame population, such as when geographic considerations are involved. For example, if the research focuses on understanding the preferences of individuals using primary care services, it is normally impractical to recruit from every primary care physician. Instead, researchers can select a sample of clusters (which in this example are primary care doctors or practices), and then randomly choose individuals from each of these clusters. The research team has to be careful to ensure that the selection of clusters does not introduce significant bias.

3.3.2 Nonprobability Sampling

Nonprobability sampling is used when it is not feasible or practical to employ probability sampling methods. In nonprobability sampling, individuals are selected on the basis of their availability or the researchers' judgement of their representativeness [61, 62]. This approach is often used in health preference research owing to cost and availability constraints. Examples include using student volunteers or recruiting eligible patients at a single hospital or clinic.

Nonprobability sampling methods are not statistically representative of the target population, and therefore the findings may not generalize beyond the specific sample used. It is important that researchers acknowledge the limitations of this approach and recognize that the results may not be generalizable to the broader population. Alternatively, they should provide justifications if they assume that health preferences do not differ between the convenient sample and the larger population they claim to represent.

3.4 Potential Sampling Issues

Sampling or selection bias refers to the situation where the actual selection probabilities differ from the assumed probabilities used in calculating the results [63]. It occurs when certain parts of the population are more or less likely to be included in the sample than others. This is particularly important when health preferences vary across the population based on certain characteristics. While we may have prior beliefs about this heterogeneity, we can only know for certain post-hoc.

If the sampling bias is owing to observable characteristics, it may be possible to address this bias by weighting the data to align the sample distribution with that of the population frame. This is a similar approach used in generalizing findings from household survey data to populations [64] and has been implemented in applied studies [65, 66]. Within preference research, a recent study by Vass et al. [67] synthesized the use of matching and weighting which can be performed in commonly used statistical software, including STATA [68] and NLOGIT [69]. However, when bias stems from unobservable or unobserved variables, it becomes challenging to adjust the results, introducing uncertainty when generalizing the findings to the target population.

Access devices used for a survey introduce another layer of sampling bias. For example, if completing a survey requires a large electronic screen (e.g., a computer or tablet), then it may be better to prevent the use of mobile phones for survey participation. Yet, this decision should be carefully balanced against the risk of losing representativeness. It may be possible to mitigate this trade-off by redesigning the survey to accommodate smaller screens, but this decision requires a careful evaluation of the advantages and disadvantages involved. A recent preference study comparing survey completions on computers versus mobile devices found that neither preferences nor choice behavior was associated with the type of device used [28].

Strategies to counter selection bias also depend on the policy question. For example, if a study seeks to explore

the preferences of health workers to remain working in healthcare, it is important that qualitative development work obtains the perspectives of those who have left for other careers [70]. When a research question aims to explore the extensive margin of a choice, respondents on both sides of the margin should be included in the study design. This inclusive approach ensures a more comprehensive understanding and mitigates the impact of selection bias.

Random sampling error refers to random variation in the results that occur owing to the random selection of elements in the sample [71]. Even if the sample selection process is free from sampling bias, health preference researchers should be aware of the presence of random sampling error, which is a common statistical phenomenon. When a subset of the population is selected for a health preference study, the results are inevitably influenced by this process of selection. Determining an appropriate sample size that reduces sampling error to an acceptable level is an ongoing topic of discussion in preference literature [72]. The context-specific factors and the desired level of precision in estimating the effects of interest are crucial considerations in determining the sample size.

Nonresponse or participation bias occurs when complete data cannot be obtained from all selected individuals [73]. It refers to situations where certain respondent characteristics predict nonresponse, such as omitting responses to nonmandatory questions or dropping out of the study before completion [74]. This can lead to systematic differences between the recruited population and the analyzed population. To address this bias, researchers can identify if the predictors of drop-out are also predictors of differences in preferences. For example, if men are more likely to drop out compared with women, and sex strongly predicts health preferences, over-sampling those more likely to drop out or adjusting the analysis may be necessary [75]. However, this approach has limitations, particularly when the sizes of the subpopulations being compared are too small, which may affect the reliability of comparisons of preferences between subgroups.

3.5 Sample Size

In health preference research, having an adequate sample size is crucial to obtaining sufficient statistical power needed to test hypotheses. The complexity of the survey instrument, such as the number of attribute levels, the number of choice tasks, and the number of alternatives per choice task has a direct impact on the sample size [76, 77]. DCE researchers often rely on established rules of thumb and experience to determine appropriate sample sizes for their studies [78–80]. A review of 56 published DCE studies revealed a wide range of sample sizes, from 100 to 300 respondents. The average DCE study had six attributes with a maximum of three levels, ten choice questions, and a sample size of approximately 260 [77].

Significant contributions to understanding sample size requirements include Yang et al. [81], which introduced an empirical formula to estimate minimum sample sizes. This formula, which is based on a meta-simulation of 32 studies, suggests that a standard-sized choice-experiment study design with six to eight attributes requires approximately 200 respondents. In addition, De Bekker-Grob et al. [72] offer a step-by-step guide for calculating minimum sample sizes needed to test hypotheses within health-related DCEs, further assisting researchers in planning their studies with adequate statistical rigor.

4 Recruitment

Recruiting participants for a preference survey can be done through a variety of methods, including directly in clinics, patient groups, or web panels. The choice of recruitment strategy depends on factors, such as the research question, and the feasibility of obtaining an appropriate sample within a reasonable timeframe, and cost. Below, we describe the common approaches and outline their respective strengths and weaknesses.

4.1 Recruitment in Clinics

One recruitment option involves conducting surveys directly in clinics, especially for individuals with less prevalent diseases. In this approach, potential participants can be identified through physician referrals, review of medical records, or recruited by placing advertisements in newspapers or flyers in waiting rooms. For example, Ozdemir et al. [82] recruited individuals who were diagnosed with dry-eye disease from the eye specialty clinic at the Singapore National Eye Centre while waiting for their regular appointment. Similarly, Vaanholt et al. [83] recruited patients recovering from revascularization procedures in the hospital bed, inviting them to complete the survey during their recovery. It is essential that patients who are approached to participate in a health preference study understand that their medical care will not be affected by their decision to participate or not. Additionally, it is important to be mindful of potential challenges, such as limited time and patient privacy concerns. Researchers must be respectful of the clinical setting and ensure that the survey process does not interfere with medical appointments or recovery periods.

One challenge in recruiting from clinics is obtaining ethics approval and administrative permits to recruit patients from the clinics for research staff who are not employed by the clinics. In addition, obtaining relevant ethics approvals and permits can be time-consuming if multiple clinics serve as recruitment sites.

4.2 Patient Advocacy Groups or Organizations

Another option for recruiting respondents is through patient advocacy groups or organizations. Typically, the patient organization sends an email to all its members, inviting them to participate in health preference surveys related to their specific condition. For example, Mohamed et al. [84] recruited respondents from the Kidney Cancer Association to participate in a patient preference survey on the benefits and risks associated with renal cell carcinoma. In this study, each completed survey was rewarded with a $20 donation to the patient group, supporting research in renal cell carcinoma. Recruiting through organized patient groups often yields higher response rates and engagement owing to the members' vested interest in the topic. However, while this method allows access to a dedicated and motivated group of individuals, the preferences and experiences of these members may differ from those of the target population, simply through membership of the group. Alternatively, researchers can also recruit participants from online patient communities or forums, as demonstrated by Weernink et al. [85] in their study on Parkinson's disease. However, a disadvantage of this approach is the inability to verify whether participants are actual patients with the condition since the diagnosis typically relies on patient self-reporting.

4.3 Survey Panels

Another approach to acquire a patient sample is from a third-party survey panel. These panels can consist of the general population or specific groups. Many survey vendors offer online panels whose members have agreed to participate in surveys at a predetermined rate, such as a certain number of surveys per month or a fixed reimbursement per survey. Panel members typically receive incentives, such as points for merchandise, entries into prize drawings, or monetary rewards (cash, checks, gift cards) [86] to enhance participation and data quality [87]. Some survey panels specialize in certain types of diseases, such as chronic illnesses, who agree to participate in web-based surveys. For instance, Hauber et al. [88] recruited UK patients with osteoarthritis from Harris Interactive's web-based chronic illness panel for a preference survey on osteoarthritis treatments.

A key advantage of using survey panels is the ability to complete research projects quickly, enabling timely responses to important questions and emerging topics. Panel providers are expected to maintain strict quality controls, and some offer the option (at a higher cost, on the basis of panel composition) to include patients with specific characteristics, such as sex, age, or disease progression. Furthermore, some survey vendors not only provide potential respondents but also host and program the questionnaires. There are, however, concerns regarding sample integrity and data quality when using survey panels. Panel membership may introduce self-selection bias, in which individuals disproportionately select themselves into a group [89], as it may only include individuals with internet access [86] or "professional survey takers" primarily interested in incentives. Some studies have implemented time criteria to exclude respondents who did not spend adequate time on the survey [90], but such strategies can be circumnavigated. In addition, it is reasonable to assume that there are unobservable or unobserved characteristics that influence panel membership as well as health preferences.

4.4 Open Platforms and Social Media

In recent years, open platforms, such as Amazon Mechanical Turk (MTurk) [91–93] and social media platforms [40, 94, 95], have emerged as popular and cheaper avenues for data collection. However, there is a mounting concern regarding the quality of data obtained through these platforms, as well as to some extent, from survey panels [96]. The proliferation of artificial intelligence (AI) technologies and bots has further exacerbated this issue, leading to an increase in fraudulent data [97]. While usability statistics offer some insights into distinguishing genuine responses from fraudulent ones, verifying the authenticity of participant data remains a challenge [97, 98]. More research is needed in this area to address these concerns and ensure the quality of data collected through online platforms.

4.5 Working with a Vendor

Researchers have the option to collect data themselves or collaborate with a data collection consultancy for data collection. Engaging a consultancy can free up researchers' time to focus on survey design and analysis, while benefiting from the consultancy's expertise and access to a larger pool of data collection staff. Programming may be aligned with a vendor recruiting participants, as discussed below.

However, several considerations should be taken into account when working with a survey vendor. First, adequate training should be provided to the staff or interviewers

involved in the survey to enable researchers to identify and address any issues with survey tools or data collection processes early on [99]. Second, regular data checking and oversight mechanisms should be in place to verify that high-quality data are being captured, for example examining the time taken to complete tasks, or behaviors indicative of a lack of attention, such as straight-lining, and choosing the same alternative in every task [100, 101].

4.6 Other Considerations

Recruitment in health preference research requires careful planning to avoid potential biases in participants' likelihood to agree to participate. Biases can arise from various factors, such as language, health status, personality, or access to technology. To mitigate these biases, researchers should be aware of how specific recruitment may introduce these biases in their target population. For example, to avoid recruitment bias in Singapore, where multiple languages are commonly spoken, Finkelstein et al. [102] conducted surveys in English, Mandarin, or Malay via face-to-face interviews, ensuring a diverse representation of participants. Another strategy to minimize biases is to employ multiple recruitment approaches, such as using survey panels, clinic-based recruitment, or media advertising. This approach allows researchers to diversify their sample sources and minimize biases associated with individual recruitment approaches. However, managing and maintaining a sampling frame in real time can be challenging.

Incentives, such as payments or rewards, are often used to encourage participation and ensure that respondents do not face any financial burden owing to their participation. Careful consideration is necessary when determining the type of incentive to offer. For instance, providing cash incentives may not be appropriate for certain groups, such as children or individuals with addiction issues. In such cases, nonmonetary options, such as vouchers, may be considered and should be selected in collaboration with relevant local ethics committees.

4.7 Pilot Testing

It is crucial to anticipate and address potential issues that may arise during survey administration. To mitigate risks and ensure quality data, a common approach is to conduct pilot testing of the survey. This involves collecting data from a small portion of the total sample and temporarily pausing recruitment. The purpose of the pilot testing is to allow the research team to evaluate and refine their assumptions about the rate of recruitment, analyze quantitative data for concerning patterns, and review responses from participants that may indicate respondent misunderstanding or poor data quality. As an aside, pilot testing is often also used to provide prior information to help develop a more efficient experimental design. More details can be found elsewhere [103].

Following the soft launch, if changes are deemed necessary on the basis of data evaluation, the research team must consider whether the results from the pilot data can be combined with the main survey data or if they need to be removed. Cosmetic or minor changes can typically be accommodated by combining both datasets. However, if substantial changes are made to the DCE design (i.e., attribute or levels, or significant changes to descriptions), participants should be omitted from the final analysis.

Robust pilot testing serves as a crucial strategy in mitigating measurement error, a bias arises when a study fails to accurately measure the underlying concepts or variables [104]. In preference research, this may occur for several reasons, including but not limited to ambiguities in attribute definitions, complexity of choice questions, features of the experimental design, and fatigue and inattention of respondents [105]. It is therefore critical to assess the quality and validity of the measures used in preference surveys. Health preference studies often involve complex cognitive tasks, leading to a proportion of the sample struggling to comprehend or respond accurately. Ozdemir et al. [101] show that certain groups, such as nonwhite, lower-income, and lower-educated individuals, may be more likely to fail attention tests included in DCE surveys. To counteract this, researchers should design surveys that minimize measurement error through high-quality qualitative work [106–108], extensive piloting among individuals from diverse social groups [109], and careful designing of the choice tasks [110–112]. Several strategies, such as time to think [113, 114], cheap talk scripts [115, 116], and statistical methods to identify poor-quality data [96] have been developed. In addition, it is important to consider this concern during sample recruitment and survey administration. While excluding individuals who fail to understand the topic or task may be considered, this may introduce an additional risk of sampling error. Therefore, it is preferable to construct health preference tasks in a way that minimizes such occurrences. Achieving this partly depends on the specific context, but actively involving potential respondents throughout the development process is important [117] and increasingly recognized as a key factor in minimizing such issues.

5 Response Rate

5.1 How to Calculate Response Rate

Response rate is calculated as the percentage of respondents who complete the survey out of the total number of individuals who were invited to participate. For example, if 120 respondents completed the survey out of 200 that are invited, the response rate would be 60%.

5.2 What is a Good Response Rate?

Evidence on response rates specifically related to stated-preference surveys is limited. However, a meta-analysis conducted by Watson et al. [118] focused on DCE studies and provided average response rates on the basis of different survey administration methods. According to their findings, the average response rates were 52% for mail surveys ($N = 64$ studies), 79% for self-administered surveys ($N = 24$ studies), 65% for moderator-administered surveys ($N = 16$ studies), 44% for online survey panels ($N = 8$ studies), and 59% for surveys that used other administration methods ($N = 20$ studies). These response rates can serve as reference points for researchers considering different methods of survey administration. However, it is important to note that these findings may not be universally applicable, and response rates can vary based on specific study contexts and populations. Notably, certain modalities, particularly online data collection using panels, may require nuanced interpretation of response rates. In instances when a survey link is distributed to a large number of potential respondents, and the survey concludes upon reaching a prespecified participant number, the response rate—computed with the total number of emails sent as the denominator—may appear extremely low. However, this might not inherently compromise generalizability.

A major concern is the lack of reporting on response rates in research manuscripts, particularly for nonmail surveys. Watson et al. [118] report that response rate information was missing for a considerable proportion of the studies: 13% of mail surveys, 38% of self-administered surveys, 56% of interview-administered surveys, 35% of internet panels, and 46% of surveys using other methods. The primary reason for this lack of reporting was the failure to record the number of invitations sent to potential participants. To address this concern, we encourage researchers to record and report the response rate, regardless of the survey method used.

5.3 How to Improve Response Rate

Improving the response rate depends on various factors, such as the target sample, recruitment method, type of survey administration, and complexity of the survey, especially that of the preference-elicitation tasks. We discuss each factor individually on the basis of our experience in this field.

The response rate is likely to be higher if the survey topic is of interest to the target sample [119]. For example, compared with the general population, cancer patients and their family caregivers are more likely to participate in a survey about cancer. On the other hand, a survey about willingness to pay for improved healthcare services might attract the general population's interest, especially if it involves taxes as a payment vehicle. Response rate may also vary by respondent characteristics [120]. For example, if the target sample consists of older and sick patients who already have a heavy burden in their daily lives, the response rate may be lower [121].

The response rate is also influenced by the recruitment method. Tailoring the approach to the characteristics of the target sample can yield better results. For example, if the target sample consists of stage 4 cancer patients, a mail survey may yield a very low response rate, while recruitment through oncology clinics may yield a better response rate. Cultural factors can also play a role in how the recruitment method affects the response rate. For example, in developed countries such as the US, where privacy is a major concern, people are not accustomed to having enumerators knocking on their door. As a result, this recruitment method may be less effective in such settings. On the other hand, in lower-income countries and rural parts of middle-income countries, people are more open to interpersonal interactions and hospitality, and may be more receptive to welcoming enumerators into their homes.

The type of survey administration can influence potential respondents' willingness to participate in the study. On the basis of our experience, older respondents generally prefer interviewer-administered or assisted surveys and are less inclined to use tablets, especially if they have lower levels of education. In contrast, younger individuals tend to favor self-administered surveys and surveys administered online. For example, in a survey with older individuals with chronic kidney disease and their family caregivers, younger family caregivers opted for completing the survey themselves without interviewer assistance while the older respondents preferred the assistance of an interviewer [102].

The complexity of the survey affects cognitive burden on respondents, which in turn affects the response rate. For example, a study by Watson et al. [118] demonstrated that inclusion of more attributes in a choice task led to a decrease in response rates while including an opt-out alternative in a choice task increased the response rates in DCE studies.

As a summary, we recommend the following steps to improve response rates:

- Keep the survey topic relevant to the target sample. Clearly explain why the survey is important and how their participation can contribute to improve research or benefit future patients. People are often altruistic and may feel satisfaction in contributing to a meaningful cause, even if they do not receive direct benefits.
- Consider the characteristics of the target sample, such as their age, health status, privacy concerns, interests, and technological proficiency, when choosing survey

administration and recruitment methods. Tailor your approach to their specific needs and preferences.
– Design survey instruments that are clean, easy to read, and simple to interpret. Avoid overburdening respondents with unnecessary questions. Streamline the survey to focus on essential information. Good piloting can help with these aspects.

6 Data Management

Effective data management is crucial for the success of any research study, including health preference studies. It involves ensuring the quality, security, and efficiency of collected data. The specific data management requirements will depend on factors, such as the data collection method, collaborations involved collecting the data, and the requirements set by institutions, funders, or employers.

When data are collected electronically, quality control measures should be implemented before data collection begins. Researchers need to ensure that data is accurately collected using appropriate electronic tools and that it is securely stored. In preference studies, where tasks can be complex, face-to-face paper-based data collection may be preferred owing to its flexibility. However, this requires data entry, which is best done through independent double entry, where two individuals enter the paper-based data into a computer database. Although this process can be time-consuming and costly, it aims to minimize coding errors after data collection.

Regardless of the data collection format, researchers or collaborators are advised to check data quality as soon as possible. Daily checks are commonly performed, and researchers should look for inconsistencies in coding, outlier data points, and patterns that may be unexpected or unlikely to occur in reality. This allows for the identification and resolution of inaccuracies and reduces the likelihood of missing or incorrect data.

6.1 Data Management Plans

A data management plan (DMP) is a document that outlines the procedures for handling research data throughout a project and after its completion. It is typically developed as part of a research proposal or within the initial 6 months of initiating a study. The purpose of a DMP is to specify all relevant aspects of data management, including the data collection process, data usage and storage methods, and the duration for which the data will be retained. It also addresses the recognition of data rights and data safety. A key aspect of data management is ensuring that research data is stored in a controlled and secure environment for the duration specified in the DMP, which is typically around 10 years. Adequate documentation should accompany the data to facilitate understanding and analysis. For those looking to create a DMP, an example template is available at the following link: [https://doi.org/10.17037/PUBS.03750331]. Although originally designed for research students, this resource can serve as a starting point for researchers at any level in developing their own DMP.

7 Conclusions

This paper has addressed several important considerations in the administration of stated-preference surveys. Various issues related to sampling frame design, recruitment, mode of survey administration, and data management have been discussed. It is important to recognize that there is no one-size-fits-all solution, and the optimal approach will depend on the specific context of the study. When administering stated-preference surveys, it is crucial to choose a method that minimizes the risk of incomplete or poor-quality data. The data collection process should align with the technical capabilities of the study setting while also ensuring that the survey does not impose unnecessary burdens on respondents.

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