

# Non Response in Scientific Research: Types, Impact and Mitigation Strategies

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### ABSTRACT

Non response in scientific research denotes the absence or refusal of sampled units to participate fully or partially in a study, posing considerable challenges that may undermine the validity and reliability of research findings. This article explores the concept of non response, its types, and its potential impact on research outcomes. It also discusses strategies to mitigate these issues. By understanding and addressing non response, researchers can improve the quality and robustness of their studies.

Keywords: Non response, Non response Bias, Survey Errors

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#### Introduction

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Researchers worldwide encounter the challenge of non response to varying degrees in their scientific studies. While ideally, every study would include the entire defined universe of interest, this approach is often impractical, time-consuming, and costly. Researchers, therefore, typically opt for a sample that is sufficiently sized and representative of the study population. However, some participants may choose not to participate for various reasons, leading to what is known as non response.<sup>1,2</sup>

In population-based longitudinal and cohort studies, non response, where participants fail to provide data at one or more follow-up points, represents a key component of attrition that can significantly affect research outcomes. Non response not only reduces the sample size and decreases statistical power but also introduces bias.<sup>3,4</sup>

Despite the plethora of research papers published across various scientific journals, few address the critical issue of response and non response rates, along with their farreaching implications, this critical aspect of the research has received scant attention.<sup>5,6</sup> Addressing this need, this paper aims to provide an overview of non response in scientific research, encompassing its types, impact, and strategies to mitigate it for improved research outcomes.

#### Non response and Types of non response

According to Gordon Marshall's Dictionary of Sociology, non response refers to the proportion of individuals invited to participate in a voluntary interview, survey, or similar study who either decline to participate or cannot be reached for various reasons. This definition also encompasses instances where participants fail to provide accurate information.<sup>7</sup> Non response covers various causes for non-participation,

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including refusals, language barriers, temporary absences (e.g., vacations), and instances where contact cannot be established, which may indicate covert refusals. In contrast, participants who fall outside the study's scope are categorized as ineligible and are excluded entirely. This group includes individuals who have passed away, relocated outside the study area, or businesses that have ceased operations.<sup>7,8</sup>

Non response in research studies can be categorized into three types:

- Unit Non response: When no response is received from a segment of the selected survey sample.
- **Item Non response:** When some questions in the survey instrument receive no response.
- Wave Non response: When participants engage in some follow-ups but miss others.

Each type of non response poses unique challenges for data quality and can lead to bias if not carefully managed.<sup>4,8,9</sup>

#### **Current scenario**

In recent years, there has been a proliferation of research studies, resulting in participants facing an increasing number of requests to participate in studies, including healthrelated research, academic investigations, commercial surveys, and political polls. This has created an oversurveyed society, contributing to survey fatigue, which in turn can be a significant contributor to non response. This issue was particularly evident during the COVID-19 pandemic.<sup>10,11</sup> Sometimes participants are offered incentives such as cash or gifts. While these incentives can boost participation rates, they also raise participants' expectations for compensation.<sup>12</sup> According to Galea and Tracy, modern epidemiologic studies often require extensive survey assessments, biological sample collections, and frequent follow-ups, which can be burdensome for participants. Over time, this can lead to a decline in participant interest and an increase in non response rates.<sup>10</sup> According to Weisberg, Krosnick, and Bowen, during the 1950s, survey researchers commonly achieved response rates of 90% or higher. However, in today's settings, response rates have significantly declined, with typical rates now falling below 70%. This decrease is largely due to growing public skepticism towards interviewers and survey requests. Even when high response rates are obtained, researchers still face many potential issues related to respondent engagement and honesty.<sup>13</sup>

#### **Participants' aspects**

Non response in research studies or surveys is influenced by both motivating and demotivating factors related to the participants. Motivating factors include the relevance of the study, incentives, ease of participation, and assurances about privacy. Demotivating factors include long or complex surveys, lack of personal relevance, privacy concerns, and issues with accessibility (e.g., lack of technology). Understanding these factors is essential for improving response rates and ensuring more representative data.<sup>14</sup>

Kristen O. raises important questions about participant involvement and response accuracy in research studies: Why do individuals choose to participate? How does their non-participation affect survey estimates? Are the responses provided by participants accurate, and is there a link between their willingness to engage and the accuracy of their responses? These questions highlight how a lack of motivation can contribute to non response, ultimately affecting the validity and reliability of survey results. Addressing these factors is critical, as non response not only distorts data but can also lead to biased outcomes, complicating the interpretation of findings.<sup>15</sup>

#### Bias arising due to non response

According to Gordon Marshal, non response is a good indicator of response bias: as a general rule, the higher the proportion of non-respondents to a survey, the greater the degree of bias among those who chose to participate. Rules of thumb for acceptable levels of survey response vary, but 60 percent would generally be regarded as the bare minimum, with 75 percent regarded as very good, and anything above that as excellent. Non response above 40 percent would normally be regarded as high enough to vitiate the results obtained from a survey or study, as non-participants roughly equal participants. When the respondents and non-respondents differ in relation to criterion measures, the results may be misleading or even erroneous.<sup>7,16</sup> A recent study in the Netherlands underscored this issue, finding that voluntary participation methods with low response rates underreported health risks such as smoking, alcohol consumption, and mental health issues. This emphasizes the importance of carefully addressing recruitment methods and non response bias in health research.<sup>2</sup>

According to Drivsholm et al., individuals who participate in health studies generally exhibit better health profiles compared to non-participants.<sup>17</sup> This disparity raises concerns about selection bias, which may skew the generalizability of findings. For example, studies involving psychiatric patients suggest that non-participants are more likely to experience severe psychiatric issues than those who agree to participate.<sup>18,19</sup>

The reliability and validity of self-reported data on medication use are influenced by several factors, including the respondent's willingness to provide accurate responses, and the robustness of the data collection methodology. Poorly structured questionnaires and unclear data collection processes can exacerbate inaccuracies in self-reported data.  $^{\rm 20,21}$ 

Non response bias can distort conclusions, particularly when the non-respondents share specific characteristics that are relevant to the study's objectives. While it is usually not possible to completely eliminate non response bias, researchers can mitigate its impact by considering it at both the design and analysis stages of their studies.<sup>22,23</sup>

## Survey errors and the critical role of non response

Dillman (2014) identifies four primary sources of error in sample survey research: sampling error, coverage error, measurement error, and non response error. They are the cornerstones for conducting a quality survey and play a critical role in shaping the reliability and validity of survey outcomes. Non response error, in particular, arises when individuals selected for the study fail to participate, leading to potential biases that compromise the representativeness of the findings. As the magnitude of any of these errors increases, the reliability of the results diminishes, undermining the study's ability to reflect the target population accurately. This erosion in accuracy highlights the need for a strategic focus on mitigating errors, especially non response errors, to uphold survey-based research's credibility and utility.<sup>24</sup>

#### Dealing with survey errors

Sampling error can be reduced by increasing the sample size but cannot be eliminated unless one conducts a census (whole population).<sup>25</sup> Coverage error occurs when the sampling frame fails to represent the entire population of interest, leading to either undercoverage or overcoverage. This error can be mitigated by improving the sampling frame and ensuring comprehensive inclusivity. Measurement error arises from flawed methods or defective, uncalibrated instruments used in data collection. This error can be addressed by employing accurate methods and properly calibrated instruments. Non response error is a critical issue in research studies, as it introduces bias and leads to results that do not accurately reflect the target population, ultimately undermining both the validity and generalizability of findings. Effectively managing non response error is essential for conducting high-quality survey research, making it one of the most significant challenges that researchers must address(Figure 1).<sup>24,26</sup>

#### **Controlling Non response**

Couper and Groves identified four key influences that affect a potential respondent's decision to participate in a survey. First, respondents are influenced by two factors beyond the researcher's control: their social environments, including personal attitudes and past experiences with surveys, and their immediate households, which can include factors like household dynamics and time constraints. Second, respondents are influenced by two factors that the researcher can control: the survey design, which encompasses the length, complexity, and relevance of the survey, and the interviewer, whose characteristics, such as professionalism and approachability, can impact the respondent's willingness to participate.<sup>26</sup>

To effectively handle non response errors, Lindner, Murphy, and Briers (2001) propose several strategies after conducting appropriate follow-up procedures and statistical significance testing. These methods include.<sup>27</sup>

- Ignoring Non-Respondents: If the non-respondents represent a small proportion of the sample population, they may be disregarded without significantly impacting the results.
- Comparing Respondents to the Population: A comparison of the survey respondents with the broader population can highlight any biases in the sample.
- **Comparing Respondents to Non-Respondents:** Analyzing differences between the two groups helps identify potential biases due to non response.
- **Comparing Early and Late Respondents:** This comparison can reveal if there is a timing bias, where those who respond later differ systematically from early responders.
- **"Double Dipping" Non-Respondents:** By selecting a random sample of non-respondents, following up with them, and statistically comparing their responses with the original respondents, researchers can assess the impact of non response bias.

Additionally, general measures to control non response error include:<sup>27,28</sup>

- Increase Response Rate: Personalize communications, use reminders, and offer incentives to encourage participation.
- Follow-Up Strategies: Persistent follow-up contacts, including reminders and alternate response methods, can increase the likelihood of responses.
- Assess Non response Bias: Comparing early versus late responders and respondents to non-respondents can uncover non response biases.
- Weighting Adjustments: Statistical techniques such as weighting can correct for biases caused by non response, making the results more representative.
- Improve Survey Design: Keep surveys concise and user-friendly. Ensure relevance and clarity in questions.

These combined strategies enhance the reliability of survey results and ensure that they accurately reflect the target population (Figure 1).



Figure 1. Types of Errors in Scientific Research and Strategies for Mitigation

Moreover, Kristen O. (2007) emphasizes that cooperation in interviewer-administered surveys is influenced by factors such as social environment, household composition, interviewer characteristics, survey design, and their interactions. Non response can be categorized into noncontact and non-cooperation, with the former being easier to manage in interviewer-administered surveys.<sup>15</sup> Non response due to non-contact can be reduced by scheduling surveys at convenient times, such as weekends, and making repeated visits. Non-cooperation can be addressed by enhancing communication, building rapport, clearly explaining the study's purpose, and offering incentives. Ensuring concise, clear questions, training interviewers effectively, and following up with non-respondents to compare respondent and non-respondent characteristics can further reduce bias. Researchers should also ensure a representative sample, test survey instruments, and apply statistical measures like Cronbach's Alpha for reliability.<sup>15,29</sup>

In today's highly surveyed society, survey fatigue has become a significant factor contributing to non response. This phenomenon occurs when participants lose motivation to complete surveys, often due to excessive length or frequency. To mitigate this issue, researchers can adopt strategies such as keeping surveys concise, implementing skip logic to ensure participants only answer relevant questions, displaying progress indicators to enhance engagement, and providing incentives—both monetary and non-monetary—to encourage participation.<sup>30</sup>

In longitudinal studies, participants may fail to continue in subsequent data collection waves, a phenomenon known as wave non response, which can compromise the validity of the findings. Major challenges in maintaining participant engagement in such studies include participant fatigue, loss of contact, perceived lack of immediate benefit, perceived burden of participation, and privacy concerns. To improve engagement, researchers can employ strategies such as regular and personalized communication, flexible participation methods, maintaining updated contact information, minimizing survey burden by keeping it concise, and building participant trust by emphasizing study benefits and providing periodic summary reports.<sup>31,32</sup>

Emerging technologies like artificial intelligence (AI) and machine learning (ML) also offer innovative solutions to mitigate non response. AI can predict the dropout participants based on their response patterns, enabling researchers to send personalized reminders to boost engagement. The use of AI chatbots can also enhance participants' engagement by answering basic queries and sending reminders.<sup>33</sup> For unavoidable non response, ML- based data imputation techniques can predict and fill the missing values while preserving data integrity.  $^{\rm 34}$ 

#### **Case Scenario**

In a study assessing the prevalence of skin morbidity among construction workers, 20.3% of participants reported skin conditions, with only 12.5% using personal protective equipment (PPE) regularly.<sup>35</sup> However, this prevalence was significantly lower than the 47.8% and 36.2% reported in other Indian studies on similar populations.<sup>36,37</sup> This discrepancy suggests potential underreporting, likely influenced by non response bias, where workers with skin conditions might have avoided participation due to concerns such as job insecurity or fear of employer repercussions. To mitigate non response and improve study accuracy, researchers should implement measures such as ensuring participant confidentiality, refining data collection methods, conducting follow-up surveys, and raising awareness about the study's importance. These strategies can enhance participation and provide a more accurate estimate of the occupational burden of skin diseases among construction workers.

#### Conclusion

This review highlights the critical impact of non response on research outcomes and emphasizes the importance of adopting tailored mitigation strategies. Future research should focus on integrating technological innovations, ethical recruitment practices, and participant-centered approaches to enhance response rates. By addressing these challenges, researchers can ensure the validity, reliability, and generalizability of their findings.

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#### References

- Ma M, Rosenberg S, Kaizer AM. The impact of nonresponse in different survey stages on the precision of prevalence estimates for multi-stage survey studies. BMC Research Notes. 2021 Dec;14:1-5.
- 2. Cheung KL, Ten Klooster PM, Smit C, de Vries H, Pieterse ME. The impact of non response bias due to sampling in public health studies: A comparison of voluntary versus mandatory recruitment in a Dutch national survey on adolescent health. BMC public health. 2017 Dec;17:1-0.
- Haapea M. Non response and information bias in population-based psychiatric research: the Northern Finland 1966 Birth Cohort study. University of Oulu; 2010 Apr 13.
- 4. Little RJ, Rubin DB. Statistical analysis with missing

data. John Wiley & Sons; 2019 Apr 23.

- Werner S, Praxedes M, Kim HG. The reporting of nonresponse analyses in survey research. Organizational Research Methods. 2007 Apr;10(2):287-95.
- Jackman S. Correcting surveys for non response and measurement error using auxiliary information. Electoral Studies. 1999 Mar 1;18(1):7-27.
- 7. Marshal G. A dictionary of sociology. Oxford: Oxford University Press; 1998.
- Čehovin G, Bosnjak M, Lozar Manfreda K. Item nonresponse in web versus other survey modes: a systematic review and meta-analysis. Social Science Computer Review. 2023 Jun;41(3):926-45.
- Vanable PA, Carey MP, Carey KB, Maisto SA. Predictors of participation and attrition in a health promotion study involving psychiatric outpatients. Journal of Consulting and Clinical Psychology. 2002 Apr;70(2):362.
- Galea S, Tracy M. Participation rates in epidemiologic studies. Annals of epidemiology. 2007 Sep 1;17(9):643-53.
- De Koning R, Egiz A, Kotecha J, Ciuculete AC, Ooi SZ, Bankole ND, Erhabor J, Higginbotham G, Khan M, Dalle DU, Sichimba D. Survey fatigue during the COVID-19 pandemic: an analysis of neurosurgery survey response rates. Frontiers in surgery. 2021 Aug 12;8:690680.
- 12. Singer E, Couper MP. Do incentives exert undue influence on survey participation? Experimental evidence. Journal of empirical research on human research ethics. 2008 Sep;3(3):49-56.
- Weisberg HF, Krosnick JA, Bowen BD. An Introduction to Survey Research and Data Analysis. Glenview. Ill.: Scott, Foresman. 1989.
- 14. Biemer PP, Lyberg LE. Introduction to survey quality. John Wiley & Sons; 2003 May 13.
- Olson KM. An Investigation of the Nonresponse-Measurement Error Nexus (Doctoral dissertation). Fox JA, Tracy PE. Randomized response: A method for sensitive surveys. (No Title). 1986 Apr.
- Drivsholm T, Eplov LF, Davidsen M, Jørgensen T, Ibsen H, Hollnagel H, Borch-Johnsen K. Representativeness in population-based studies: a detailed description of non response in a Danish cohort study. Scandinavian journal of public health. 2006 Dec;34(6):623-31.
- Fischer EH, Dornelas EA, Goethe JW. Characteristics of people lost to attrition in psychiatric follow-up studies. The Journal of nervous and mental disease. 2001 Jan 1;189(1):49-55.
- Vanable PA, Carey MP, Carey KB, Maisto SA. Predictors of participation and attrition in a health promotion study involving psychiatric outpatients. Journal of Consulting and Clinical Psychology. 2002 Apr;70(2):362.
- Caskie GI, Willis SL. Congruence of self-reported medications with pharmacy prescription records in low-income older adults. The Gerontologist. 2004 Apr

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1;44(2):176-85.

- 20. Klungel OH, de Boer A, Paes AH, Herings RM, Seidell JC, Bakker A. Influence of question structure on the recall of self-reported drug use. Journal of clinical epidemiology. 2000 Mar 1;53(3):273-7.
- 21. Cobanoglu C, Ciccarelli S, Nelson RR, DeMicco FJ. Using global positioning systems as a marketing tool: An analysis of US consumers' use and perceptions. Journal of Hospitality Marketing & Management. 2010 Jul 14;19(6):556-74.
- 22. Barribeau P, Butler B, Corney J, et al. Survey research. Writing@CSU. Colorado State University; 2005. Available at: https://writing.colostate.edu/guides/ guide.cfm?guideid=68.
- 23. Dillman DA, Smyth JD, Christian LM. Internet, phone, mail, and mixed-mode surveys: The tailored design method. Indianapolis, Indiana. 2014.
- 24. Tyrer S, Heyman B. Sampling in epidemiological research: issues, hazards and pitfalls. BJPsych bulletin. 2016 Apr;40(2):57-60.
- 25. Groves RM, Couper MP. Nonresponse in household interview surveys. John Wiley & Sons; 2012 Aug 29.Lindner JR, Murphy TH, Briers GE.
- 26. Handling nonresponse in social research. Journal of agricultural education. 2001 Dec 31;42(4):43-53.
- Miller P, et al. A systematic review of nonresponse bias studies. Available at: https://nces.ed.gov/fcsm/pdf/A\_ Systematic\_Review\_of\_Nonresponse\_Bias\_Studies\_ Federally\_Sponsored\_SurveysFCSM\_20\_02\_032920. pdf (Accessed 30 November 2024).
- 28. Santos JR. Cronbach's alpha: A tool for assessing the reliability of scales. The Journal of Extension. 1999;37(2):15.
- 29. Ghafourifard M. Survey Fatigue in Questionnaire Based Research: The Issues and Solutions. Journal of Caring Sciences. 2024;13(3):148-9.
- Teague S, Youssef G, Macdonald J, et al. Retention strategies in longitudinal cohort studies: A systematic review and meta-analysis. BMC Med Res Methodol. 2018;18(1). https://doi.org/10.1186/s12874-018-0586-7.
- Abshire M, Dinglas VD, Cajita MI, Eakin MN, Needham DM, Himmelfarb CD. Participant retention practices in longitudinal clinical research studies with high retention rates. BMC medical research methodology. 2017 Dec;17:1-0.
- 32. Collins J, Kern C. Longitudinal nonresponse prediction with time series machine learning. Journal of Survey Statistics and Methodology. 2025 Feb;13(1):128-59.
- 33. Wang H, Tang J, Wu M, Wang X, Zhang T. Application of machine learning missing data imputation techniques in clinical decision making: taking the discharge assessment of patients with spontaneous supratentorial

intracerebral hemorrhage as an example. BMC Medical Informatics and Decision Making. 2022 Dec;22:1-4.

- 34. Trivedi A, Patel Y, Pandit N, et al. Prevalence of skin morbidity among construction site workers working at Vadodara. Healthline. 2011;2(1). Available at: https://www.cabidigitallibrary.org/doi/ pdf/10.5555/20113327903
- Shah KR, Tiwari RR. Occupational skin problems in construction workers. Indian journal of dermatology. 2010 Oct 1;55(4):348-51.
- Banerjee M, Kamath R, Tiwari RR, et al. Dermatological and respiratory problems in migrant construction workers of Udupi, Karnataka. Indian J Occup Environ Med. 2015;19(3):125. https://doi.org/10.4103/0019-5278.174001.