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Propensity Score Adjustment (PSA)weighting technique for reducing bias in web panel surveys

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Abstracts
This study focuses the Propensity Score Adjustment (PSA) technique for reducing bias in web panel surveys. Web panel surveys have become increasingly popular in recent years due to their convenience, time and cost-effectiveness. However, they are prone to various sources of bias, including nonresponse bias, selection bias, and measurement bias. PSA is a statistical technique that can be used to adjust for these biases by weighting the data based on a participant's propensity score, which is a measure of their likelihood of being included in the sample. The study's application involved collecting data through web panel surveys on "Usage of social networking sites in education: a case study on International Islamic University Chittagong (IIUC)". The PSA technique was employed to adjust for potential selection bias that may arise from the non-random selection of participants in the web panel. The study concludes by highlighting the efficacy of utilizing PSA in web panel surveys and offering recommendations for its implementation.

Keywords PSA technique, Web panel surveys, Selection bias, Nonresponse bias, Reducing bias.

Paper type Research paper

1. Introduction

Web surveys have grown in popularity recently because they offer an interesting and appealing tool for gathering data (Khan, 2023). It gives the researchers quick access to a huge pool of possible responders at a reasonable cost. The computer-assisted interviewing (CAI) approach has largely supplanted the original and most conventional data gathering method, paper and pencil interviewing (PAPI) (Couper, 2005). According to Bandilla, Bosnjak, & Altdorfer (2003); Couper, Kapteyn, Schonlau, & Winter (2007); and Dever, Rafferty, & Valliant (2008) "Web surveys have gradually replaced face-to-face surveys (CAPI), computer-assisted telephone surveys (CATI), and postal surveys (CASI, CSAQ) as the most popular conventional data gathering methods. It is hardly unexpected that internet research has gained appeal and

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acceptability. An online survey is a method for reaching a huge number of potential participants over the internet. Web panel surveys refer to a research method where a group of individuals is selected from online platforms. Data are collected from the selected individuals through online questionnaires or other web-based methods. According to Dillman, Smyth, & Christian (2014), web panel surveys are "a type of online survey that uses a pre-recruited, non-probability sample of individuals who agree to participate in multiple survey administrations over time". It consists of a range of approaches with various objectives, target populations, target groups, etc. By eliminating the need for interviewers or paper-based questionnaires and lowering the survey's printing and/or postage expenses, questionnaires may be disseminated to a large number of people at a cheap cost. Web surveys may get underway fairly quickly. Compared to traditional research, it requires little or no time between creating the questionnaire and beginning the fieldwork. Aesthetic questionnaires may be created by employing multimedia content, including images, sounds, animations, and movies thanks to the modern possibilities offered by these surveys. Web surveys may seem to provide many more features than conventional ones, but they are only another way to collect data. Interviewers are not necessary for the online questionnaires. The individuals fill out the questionnaire online. Web surveys are subject to several issues, such as coverage, self-selection, and nonresponse errors, as highlighted by various scholars (Bethlehem, 2010; Lee, & Valliant, 2009; Fricker, 2008; & Duffy, Smith, Terhanian, & Bremer, 2005).

The Undercoverage error of an online survey arises from the inability of certain individuals to participate due to limited or no access to the internet. Individuals who utilize the internet are considered to be part of the online populace. Steinmetz, Tijdens, & de Pedraza (2009) suggest that potential biases may exist beyond discrepancies in internet access among respondents, including factors such as age, gender, educational attainment, socioeconomic status, and behavioral characteristics. According to Bethlehem (2010), there exists a positive correlation between age and education level with access to the internet, whereby younger individuals and those with higher education levels tend to have greater frequency of internet access compared to older individuals and those with lower education levels. The presence of inference bias may manifest if particular demographic cohorts (e.g., age, gender, race, education) are not adequately represented.

The phenomenon of over-coverage in web surveys may occur when participants are motivated to take part in research multiple times as a result of incentives. The prevalence of multiple email addresses among respondents is a frequently observed phenomenon that has the potential to exert influence the outcomes of web-based surveys. It might be challenging to identify specific responders in an online survey. As a result, an online survey will likely have an over-coverage issue. However, it is often believed that this issue could be more serious.

The nonresponse error occurs when individuals within a specific sample fail to provide necessary information. Nonresponse can be seen as a crucial issue when there is a substantial disparity between the answers given by responders and those who did not respond. Steinmetz, Tijdens, & de Pedraza (2009) have posited that the nonresponse rate and the distinction between responders and non-respondents influence the extent of nonresponse bias. The phenomenon of nonresponse error exhibits a positive correlation with a reduction in response rates, mainly when the rationales behind the nonresponse are linked to the predetermined research inquiries. The nonresponse tendency, while distinct from that observed in web surveys, can pose a significant challenge when response rates are comparatively lower than those observed in other survey models (Kaplowitz, Hadlock, & Levine, 2004; Shih, & Fan, 2008).

The issue of selection in web panel surveys pertains to the potential introduction of bias when individuals who are not randomly selected engage in the survey. Web panel surveys are carried out by enlisting a cohort of persons who willingly choose to partake in surveys for a designated duration. Nevertheless, it is important to acknowledge that this particular sample may not accurately reflect the characteristics and behaviors of the broader community. The process of selecting participants for this study could have been influenced by several factors, including the method used to recruit individuals, the incentives provided, and the possibility of nonresponse from potential participants. According to Couper (2013), weighting adjustments can account for demographic differences between the sample and the population, and propensity score matching can identify similar individuals in the population to compare with the survey participants. Heerwegh, & Loosveldt (2008) noted that differences in response quality between face-to-face and web surveys may also contribute to selection bias. Krosnick & Chang (2001) found that while web surveys can yield results comparable to those from telephone surveys, care must be taken to address the selection problem in order to ensure the validity of the findings.

These problems may lead to biased parameter estimations. As a result, mistakes might be made when taking an online survey. Undercoverage is a type of error that may arise in web surveys when the target population exceeds the subset of individuals who possess internet access. According to Steinmetz, Tijdens, & de Pedraza (2009) if there is no variation between individuals with internet access and those without it, the estimations of parameters will be biased. Second, self-selection implies that participation in web surveys is optional. In web surveys, participants choose themselves independently. The study's questionnaire is simply posted on website or websites. Respondents who have access to the internet visit website or web page and choose to take the survey. In comparison to the non-participants, these participants are very different. And last, measurement errors are the discrepancy between a quantity that has been measured and its true value. It involves both random and intentional mistakes. If repeated measurements yield results that may differ from the actual value of the quantity, then there is a random error. This inaccuracy could be brought on by the measurement tools' imprecise accuracy (Bandilla, Bosnjak, & Altdorfer, 2003; Fricker, 2008; & Malhotra, & Krosnick, 2007). If repeated measurement yields result that consistently occur, it is said to contain systematic errors. This could be brought on by a miscalibrated instrument that has an impact on all survey measures. Due to the rise in one-person families and dual-income households, it is now more difficult to obtain information from people (Lee, 2011). The interviewers find it challenging to meet these people throughout the day, and a growing concern for privacy is another major issue with doing traditional surveys. In order to decrease biases in online panel surveys (Undercoverage, self-selection, or nonresponse), this study assesses the efficacy of the propensity score adjustment (PSA) approach.

When the sample is not chosen randomly, a PSA weighting adjustment may be necessary to achieve accurate estimations of population characteristics. The sampling weights must be calculated as a result. This weighting's goal is to lessen estimate variation rather than to lessen or eliminate bias. You may use the weighting modification approach to increase the accuracy of your estimates. Additionally, it makes a weighted sample representative of some auxiliary variables and is frequently used to reduce bias brought on by nonresponse, coverage, and sampling errors.

The objective of this study is to evaluate the effectiveness of Propensity Score Adjustment (PSA) weighting technique in reducing bias in web panel surveys. This study addresses the challenges associated with bias in web panel surveys and to improve the quality of survey data by utilizing the PSA weighting technique. This research employs a web panel survey that is non-probability-based, namely a self-selection web survey, to conduct a case study on the International Islamic University Chittagong (IIUC). The research was undertaken with the objective of offering evidence to support a study on the effective utilization of “social networking sites” in higher education to enhance students' knowledge and learning.

The novelty of the study lies in its ability to adjust for potential confounding variables that may affect survey results. While PSA has been used in other research contexts, its application to web panel surveys is relatively new and has shown promising results in reducing bias.

Web panel surveys are subject to various sources of bias, including selection bias, nonresponse bias, and measurement bias. The PSA technique addresses selection bias by adjusting for potential confounding variables that may affect the likelihood of participation in the survey. By doing so, the technique can minimize the impact of self-selection bias and increase the representativeness of the sample.

While other techniques such as weighting and imputation have been used to reduce bias in web panel surveys, PSA has the advantage of being able to adjust for multiple potential confounding variables simultaneously. This makes it a valuable tool for researchers who are interested in obtaining more accurate and reliable survey results.

Overall, the PSA weighting technique for reducing bias in web panel surveys lies in its ability to address the unique challenges and sources of bias associated with web panel surveys, and its potential to improve the accuracy and representativeness of survey results.

2. Literature review

An innovative step in the evolution of data-gathering methods is using online surveys to extract data from the surveys. Admittedly, data collection and summary creation are highly ancient approaches. However, even in ancient times, kings used statistics to inform complex judgments that affected the country. Moreover, it is not unexpected to see that statistics continue to have a significant impact on our rapidly changing society today.

Due to their advantages, web surveys are crucial for gathering survey data. They provide quick, low-cost, and easy interviews with many possible candidates (Clayton & Werking,1998). As anticipated, more web surveys have been undertaken over time. There are, however, specific methodological issues as well. For example, several web surveys use nonprobability sampling techniques because the population's interpretation of survey data needs to be more credible.

Over the past few years, as ICT has advanced dramatically, survey research has seen a fast transformation. As a result, there has been a heated debate concerning the validity of online surveys for collecting sample data in research (Couper, 2000; Fricker, & Schonlau, 2002; Ilieva, Baron, & Healey, 2002; Tingling, Parent, & Wade, 2003; Tuten, Urban, & Bosnjak, 2002). There are several advantageous effects associated with the use of online surveys. These include cost savings, efficient data gathering, accurate result processing, adaptable questionnaire design, and the capability to reach target respondents worldwide.

Typically, gathering survey data is a challenging, inexpensive, and quick process. Throughout the history of survey research, attempts have been made to reduce costs and time while retaining the quality of the hasdata. The development of information and communication technologies made computer-assisted interviewing (CAI) possible. An electronic questionnaire was used in place of the paper form. In this instance, data are gathered quickly, cheaply, and with excellent quality. Couper, & Triplett (1998) stated that the CAI technique has advantages.

In order to conduct surveys of respondents who have internet access, one data-gathering instrument is the internet. Web surveys allow participants to independently reply to questions regarding the electronic questionnaire while collecting data via a web browser. Through a link to a web page, the survey may be accessed. Because more people in industrialized nations use the internet, web surveys are becoming more viable Crawford, Couper, & Lamias (2001). It is a relatively novel approach. Given the short timeframe and low cost, it is a suitable approach to collecting data (Couper, 2005). Because of this, the use of web surveys has increased significantly, but their methodology has yet to keep pace with this growth. This issue will be solved when web surveys are reliable and have a hypothesis that holds up in the scientific community. Therefore, the statistical study mentioned will be significant in the future. According to Toulouse, Conrad, & Couper (2013), web surveys are now an essential research instrument for various study domains, including marketing, social science, and government statistics.

Compared to postal surveys, web surveys appear to have lower response rates (Crawford, Couper, & Lamias, 2001). The lower response rates in web surveys can be attributed to various factors. The need for more useful strategic information to raise the response rate is employ persuasive and personalized communication in invitations, emphasizing the survey's relevance and impact, and consider offering small incentives to motivate participants. Additionally, keep the survey concise and user-friendly, optimizing it for mobile devices, and send timely reminders to non-respondents to encourage completion. In addition, internet users are growing increasingly irritated by the enormous load on web connections.

Couper (2005) demonstrated that until recently, only paper-and-pencil personal interviewing (PAPI) surveys or mail surveys had been used to acquire survey data. Unlike mail surveys, which are conducted as self-interviews, PAPI surveys are conducted with interviewers. Additionally, as telephone use increased among homes, telephone surveys have become increasingly popular for gathering survey data.

Undercoverage is the issue that web surveys run into more frequently. An online survey is only possible for respondents with an internet connection. Therefore, the target demographic is only covered by those with internet connections. According to Steinmetz, Tijdens, & de Pedraza (2009), the disparities in their demographic traits, as well as internet access, are further factors that may contribute to the potential bias. According to Bethlehem (2010), younger people with higher levels of education have more access to the internet than older adults with lower levels of education. Unrepresented demographic groupings may result in issues with decision-making bias.

According to Cobben, & Bethlehem (2005), overcoverage may also affect web surveys. It may happen if consumers take advantage of incentives to do several web surveys. People sometimes use many e-mail addresses, making identifying specific responders in an online poll challenging. However, it is believed that this issue is insignificant.

Specific methods can help to lessen the Undercoverage bias issue. The first step is to provide internet services to sample participants who lack internet access. They might not be interested in using the internet. Therefore, this method might not fix the issue. Second, another strategy is to conduct a mixed-mode survey. If individuals cannot access the internet, they may still gather data through the mail, do in-person interviews, or use computer-assisted interviewing. The third stage is to implement some of the adjustment weighting strategies. By employing weights, under or overrepresented strata can rectify bias. However, the weighting modification cannot guarantee that the estimate's bias will be removed.

Bethlehem (2010) demonstrated that self-selected samples from volunteer web surveys are biased estimators in theory but may have unbiased estimators. Therefore, the choice must have solid structural assumptions to be legitimate (Lee, 2004). Because the survey researcher does not know the selection probabilities, they have no control over the self-selection. A variety of methods can lessen self-selection bias. It can be first selected a suitable sample using a probability sampling strategy. Implementing the proposed weighting modification strategies is the second effort. Weights are used to correct the sample's answer for under or overrepresented strata.

A nonresponse error occurs when certain sample members need to provide crucial data. Nonresponse may be a severe issue if responders' replies differ considerably from those of non-respondents. According to Steinmetz, Tijdens, & de Pedraza (2009), the percentage of nonresponders and the gap between non-respondents and respondents in the sample influence the degree of nonresponse bias.

The extent of bias in web surveys exhibits variability. In contrast to alternative approaches for data collection, web surveys exhibit a comparatively diminished rate of response. Lozar, Manfreda, Bosnjak, Berzelak, and Kukar-Kinney (2008) found that the utilization of the online mode in surveys is associated with a reduction in the nonresponse rate by around 11% compared to conventional survey approaches. The low response rate observed in web-based surveys can be ascribed to various factors, including the implementation of follow-up contacts and incentives, technological challenges such as the use of sluggish or low-end browsers and unstable internet connections, limitations in personal computer accessibility, and concerns over privacy and confidentiality (Steinmetz, Tijdens, & de Pedraza, 2009). Since the selection probabilities of the items in the volunteer panel online survey are unknown, it is impossible to calculate the actual nonresponse rate. However, nonresponse bias might pose a severe issue in web surveys. Therefore, it is challenging to identify nonresponse. Therefore, missing at random (MAR) represents nonresponse in this study. Because they are convenient and affordable, web panel surveys have grown in popularity over the past ten years. However, nonresponse bias, which can result in erroneous estimations of population characteristics, is one of the main issues with web panel surveys. To lessen nonresponse bias, academics have recently suggested various weighting approaches. The PSA weighting method is one such method.

The PSA weighting approach has been proven in several studies to be successful in lowering nonresponse bias in online panel surveys. In an online panel survey on consumer confidence, for instance, Bethlehem, Biffignandi, Chauvin, Pennec, & Pfeifer (2011) showed that the PSA weighting approach reduced nonresponse bias. In addition, an online panel survey on political engagement conducted by Heerwegh, & Loosveldt, (2014) revealed that the PSA weighting approach minimized nonresponse bias.

A study by Wang and Heerwegh (2019) revealed that the PSA weighting method successfully lowered nonresponse bias in a web panel survey on family income. Finally, an online panel survey on consumer sentiments conducted by Kaczmirek, & Lenzner, (2018) revealed that the PSA weighting approach successfully lowered nonresponse bias.

In an online panel survey on health, research by Toepoel, Lugtig, & Tourangeau (2015) discovered that the PSA weighting approach successfully decreased nonresponse bias. According to the scientists, the strategy lessened the bias in the mean and variance of the health measurements.

In their recent study, Ferri-García and Rueda (2022) examined the matter of selection bias in web surveys. They put up the suggestion of employing variable selection approaches to identify the optimal subset of variables for propensity score adjustment calculation. This approach aims to yield estimates that are both less biased and more efficient.

Lee (2006) evaluated the effectiveness of PSA in removing bias in web panel surveys addressing sensitive health behaviors, specifically sexual health and found it effective method for reducing bias in web panel surveys.

Online surveys are popular for data collection but suffer from biased samples due to nonprobabilistic sampling. Statistical matching and PSA are proposed approaches to mitigate this bias by using a probabilistic reference sample and estimating population values through machine learning models and propensity weights (Castro-Martín, del Mar Rueda, & Ferri-García, 2022).

Ferri-García, & Rueda, (2020a) addressed the issue of selection bias in online surveys and explored the use of PSA to control this bias. It compares the effectiveness of logistic regression and Machine Learning (ML) classification algorithms for estimating propensity scores and removing selection bias in two simulation scenarios.

In their work, Ferri García and Rueda García (2020b) employed a methodology that involved the utilization of PSA and calibration techniques for both correlated and noncorrelated variables. Additionally, the researchers examined the effectiveness of a reference survey for the purpose of calibration. The findings of the study indicate that the combination of PSA and calibration techniques effectively mitigates bias. Furthermore, the utilization of population totals derived from a reference survey does not have a discernible impact on the accuracy of estimates.

The utilization of web surveys has gained significant popularity owing to their inherent benefits in the realm of data gathering. However, it is important to acknowledge that these surveys are susceptible to bias, mostly stemming from two key factors: limited coverage and self-selection. This study examines various adjustment weighting techniques, including propensity score adjustment and calibration adjustment, in order to mitigate bias in web-based surveys. The evaluation of the methodology involves a comparison between web survey results and face-to-face survey results for the Social Survey conducted by Statistics Korea. Different variable selection methods and propensity score weighting methods are considered (Lee, 2011).

Valliant & Dever (2011) proposed a method for adjusting the volunteer sample to account for nonresponse bias and coverage bias, involving the estimation of propensity scores and the application of weights based on these scores.

In their study, Liu, Zheng, Tu, and Pan (2022) employed a model-averaging estimation technique to estimate population parameters using volunteer online survey samples. This strategy involved utilizing propensity score estimates derived from both a parametric logistic regression model and a nonparametric generalized boosted model.

The use of the PSA represents a statistical methodology that can effectively mitigate the presence of selection bias within web panel surveys. PSA entails the estimation of a propensity score, which represents the likelihood of an individual being chosen for participation in a survey based on their observed attributes. The utilization of the propensity score enables the adjustment of survey data through the application of weighting or matching techniques, which aim to account for individuals who possess comparable values on the propensity score (Khan, 2018).

According to Loosveldt, & Sonck, 2008 and Schonlau, Van Soest, Kapteyn, & Couper (2009), PSA is a recommended alternative to statistically significant intrinsic problems in online survey data. The aim of the PSA is to compensate for disparities brought about by individuals' varying propensities to participate in online surveys (Duffy, Smith, Terhanian, & Bremer, 2005).

The PSA weighting technique has been identified as a promising method for mitigating biases in web panel surveys. The respondent weights are adjusted using the PSA methodology. The utilization of the PSA weighting approach has proven to be an effective technique for reducing biases during the implementation of web panel surveys. This approach has demonstrated its efficacy in numerous investigations.

3. Methodology of the study

The purpose of this study is to assess the efficacy of the PSA technique in reducing biases in web panel surveys. The study uses a non-probability-based web panel survey, a self-selection web panel survey. The survey, titled "Usage of Social Networking Sites in Education: A Case Study on International Islamic University Chittagong (IIUC)," was carried out for research purposes to support a study on how social networking sites can be effectively used in higher education to enhance student's knowledge and learning. The respondents are students from IIUC who are part of an online panel. The students who made up the web panel were enrolled in one of the six faculties at the IIUC, including the Faculty of Shariah and Islamic Studies, the Faculty of Science and Engineering, the Faculty of

Business Studies, the Faculty of Social Science, the Faculty of Law, and the Faculty of Arts and Humanities.

The response variable is the aim variable, "use of social networking sites in schooling." The study's chosen auxiliary variables are viewed as predictors. The survey consists of 26 questions, with questions 1 through 7 about demographics and 8 through 26 concerning using social networking sites in education. The survey was created as an online questionnaire with the help of Google Forms, and was then published on the IIUC website for participation. The population of this research is the whole student body of the IIUC in the spring of 2023. Since all IIUC students have access to the internet for online course registration, all IIUC students were included in the study. Therefore, 12000 (N) is the intended population size. 1920 (n) students in all took part in the survey. Only the seven demographic auxiliary variables were used in this study to estimate the target variable. They are gender, age, area, students' employment status, students' marital status, study program level, and study faculty.

3.1. Variable description

This study employed only seven demographic auxiliary variables to estimate the target variable. The gender of the respondent is indicated by the initial auxiliary variable, which is classified into two distinct categories: male and female. The age of the respondents was categorized into four groups: below 20 years, 20-25 years, 25-30 years, 30-35 years, and 35 years and above. The region of the respondent can be classified into two distinct categories: rural and urban. Employment status can be classified into three distinct categories, namely, nonemployment, part-time employment, and full-time employment. The variable representing the marital status of the respondents encompasses three distinct categories, namely single, married and divorced. The program level of the study is categorized into three distinct tiers, namely diploma, four-year bachelor's degree, and master's degree. The study includes a faculty variable that encompasses six distinct categories: Shariah and Islamic Studies, Social Science, Business Studies, Science and Engineering, Law, and Arts and Humanities.

3.2. Propensity Score Adjustment (PSA)

In order to address intrinsic problems that are statistically significant in web survey data, propensity score adjustment (PSA) is advised (Loosveldt and Sonck 2008; Schonlau et al. 2009). The PSA's goal is to eliminate disparities brought about by people's varying propensities to participate in online surveys (Duffy et al. 2005). The demographic and "webographic" (lifestyle/attitudinal) factors assessing how the web sample differs from the overall population are adjusted for selection bias, which is seen in both of these variables (Schonlau et al. 2007).

Propensity scores are generated by modeling a variable that denotes the participation of an individual or member in the survey. The dependent variable in the logit regression model is represented by a dichotomous indicator variable, while the explanatory variables consist of demographic factors. The logit regression model is employed to fit the observed sample data, and the auxiliary variables' values are utilized to compute the propensity score condition, which represents the likelihood of survey participation. It is believed that each of the k elements in the target population possesses an uncertain and unidentifiable probability of engaging in the survey. It is denoted by ρ_k, for $k =1, 2, ..., N$. Suppose, indicator variables are denoted as $R_1, R_2,..., R_N$, where, $R_k =1$, if k^{th} individual participates in the web survey, otherwise, $R_k = 0$. Thus, $P (R_k=1) = \rho_k$.

In the context of the survey participants, the propensity score is a measure of the conditional likelihood associated with an individual exhibiting X trait, as specified below:

$$\varrho(X)=P\,(R = \frac{1}{x}) \tag{1}$$

The values of the observed qualities X make up strata. It is presumed that each stratum member has an equal probability. It is known as the MAR assumption. Other names for this presumption include homogeneity (Imbeans, 2004), selection on observables (Barnow et al., 1980), notconfoundedness assumption (Rosenbaum and Rubin, 1983), and conditional independence assumption (Lechner, 1999). Usually, utilizing logit regression model (Lee, 2004; Bethlehem, 2010; Schonlau et al., 2007; Steinmetz et al., 2009; & Loosveldt and Sonck, 2008), the propensity score is computed by

$$log(\frac{\rho(X_k)}{1-\rho(X_k)}) =\alpha + \beta' X_k \tag{2}$$

A maximum likelihood estimate is performed to fit the model. Stratifying the population allows for the calculation of the propensity scores. Strata are made in a way that makes them homogeneous within them and heterogeneous between them. As a result, each level's components have almost identical propensity scores. If there is a difference in the response tendency of each item within a stratum, there will be bias. If propensity scores have five levels, a large degree of bias will be eliminated (Lee, 2011). Theoretically, the bias should be reduced by propensity score weighting. The propensity score is a measure that is often integrated with other (demographic) variables throughout a subsequent continuing weighting operation, albeit this is not how it works in practice (Schonlau et al., 2004).

The logit model is commonly employed to estimate response propensities, which refer to the likelihood of survey participation. The revision of model (2) results in the formulation

$$\rho(X_k)=\frac{exp\ (\beta' X_k)}{1+exp\ (\beta' X_k)} \qquad (3)$$

for the probabilities. The estimation of response propensities relies on the availability of data as well as the inclusion of both nonresponders and nonrespondents' values for the auxiliary variable X. The term "matching assumption" is used to describe this concept. It defines that $0 < \rho(X_k) < 1$. This assumption posits that, for any value of the auxiliary variable X, there exist persons who opt to partake in the web survey and individuals who opt not to partake in the study. It is noteworthy to mention that the likelihood of participants offering a response is binary, with a probability of either 0 or 1. A comparative analysis is not feasible due to the absence of comparable individuals for comparison. The notation $\varrho(X_k)=1$ means that the k^{th} individual participates in the study, and $\varrho(X_k)=0$ indicates that the k^{th} individual does not participate in the survey. However, regrettably, they have never been observed. Hence, this is the underlying cause of bias. This phenomenon is commonly referred to as selection bias. According to Schonlau et al. (2004), the utilization of logit regression modeling estimates can effectively mitigate potential selection bias in response propensities. The utilization of "response propensity weighting" and "response propensity stratification" are two distinct approaches within the framework of the PSA.

The evaluation of each weighting model is conducted by analyzing its performance in reducing the percentage bias of the target variable. The formula for computing percentage bias reduction, as defined by Lee (2011), is as follows:

$$p.\,bias(\hat{\theta}_{W.A}) = \left[\frac{|bias(\hat{\theta}W.U)| - |bias(\hat{\theta}W.A)|}{|bias(\hat{\theta}W.U)|}\right] \times 100\ , \ \ldots\ldots\ldots \quad (4).$$

where, $bias(\hat{\theta}W.U)$ is the unadjusted estimate and $bias(\hat{\theta}W.A)$ is an adjusted estimate in the web panel survey.

4. Results and discussion

This section represents the results and discussion of this study sequentially. The first percentage analysis is given below according to the selected auxiliary variables.

Table I.
Percentage distribution of responses of selected variables for the web panel survey

Variable	Category	Number of responding	Percentage (%)
Gender	Male	1152	60.00
	Female	786	40.00
Age (year)	<20	120	6.25
	20-25	949	49.43
	25-30	518	26.98
	35+	333	17.34
Region	Rural	795	41.40
	Urban	1125	58.60
Working status	Not working	1556	80.00
	Part-time working	250	13.02
	Full-time working	114	5.94
Marital status	Not married	1530	79.69
	Married	1165	19.27
	Divorced	20	1.04
Level of program in the study	Diploma	8	1.05
	Four-year Bachelor's degree	1620	84.37
	Master's degree	280	14.58
Faculty in the study	Shariah and Islamic Studies	154	8.02
	Social Science	269	14.01
	Business Studies	576	30.00
	Science and Engineering	384	20.00
	Law	235	12.23
	Arts and Humanities	302	15.73
Total		**1920**	

Table I presents the percentage distribution of the data obtained from the web panel survey. The target variable under investigation is the use of SNSs within the context of education. The sample size of the web panel is 2920. The initial auxiliary variable, gender, is dichotomously classified into two distinct categories: male and female. The proportion of male participants (60%) exceeds that of female participants (40%). The age group with the highest response rate, at 49.43%, is 20-25 years, while the age group with the lowest response rate, at 6.25%, is less than 20 years. Of the total respondents, 41.40% are from rural regions, while 58.60% are from urban areas. Most respondents (80%) are unemployed, while a small proportion (5.94%) work full-time. Additionally, a minority of respondents (13.02%) are employed part-time. The percentage of respondents who have never been married or are now single is 79.69%, while the percentage of respondents who are married is 19.27%. The remaining 1.04% of the respondents reported being divorced. The rate of individuals holding a diploma degree is 1.05%, while the majority, 84.37%, have a four-year bachelor's degree, and 14.58% have obtained a master's degree. Maximum respondents, comprising 30%, are affiliated with the business studies faculty, while the lowest proportion of respondents, accounting for 8.02%, are associated with the Shariah and Islamic studies faculty.

Table II

The percentage of usage of SNSs in the education for the web panel surveys

Category	Frequency	Percentage (%)
No	634	33
Yes	1286	67
Total	1920	100

Table II illustrates the comprehensive utilization of SNSs in the educational context among the web panel sample for the specified variables. According to the results of the web panel surveys, it was found that out of a total of 1920 students, 67% or 1286 students utilized SNSs for educational purposes, while the remaining 33% or 634 students did not use SNSs for educational purposes.

Table III

PSA estimation of the target variable for reducing the bias in the web panel survey

Weighting model	Estimate (%)	Standard error
No weighting	67.00	0.9060
1. Gender	68.87	0.9067
2. Age	67.51	1.1917
3. Region	67.02	0.9156
4. Working status	68.04	0.9050
5. Marital status	67.02	0.8961
6. Level of the program in the study	69.97	0.8024
7. Faculty in the study	67.85	0.9241

Table III represents the web panel surveys' estimate of the target variable. Logistic regression was employed to construct the seven PSA models that exhibited statistical significance. According to Munshi, Mostafa, and Alam (2018), 70% of Rajshahi University postgraduate students use social media in their studies. The PSA weighting correction demonstrates superior performance in weighting model-1 and model-6, in comparison to model-2, model-3, model-4, model-5, and model-7. The achieved performance is approximately 70%. The majority of weighting models mitigate bias to a certain extent, albeit not entirely. Simultaneously, it has decreased the standard error of the estimation. Several studies have used PSA to reduce selection bias in web panel surveys. For example, a study by Yeager, Krosnick, Chang, Javitz, Levendusky, Simpser, & Wang (2011) found that PSA was effective in adjusting for nonresponse bias in a web panel survey on smoking behaviors. Similarly, de Leeuw, Hox, & Scherpenzeel (2019) used PSA to adjust for self-selection bias in a web panel survey on attitudes toward immigration. Both studies showed that the PSA technique improved the accuracy of the estimates and reduced bias in the results.

Table IV
Percentage of bias reduction of the estimate of the target variable by the PSA for the web panel surveys

Weighting model	Estimate (%)	Bias Reduction (%)
No weighting	**67.00**	**-**
1. Gender	68.87	**62.33**
2. Age	67.51	17.00
3. Region	67.02	0.67
4. Working status	68.04	34.67
5. Marital status	67.02	0.67
6. Level of the program in the study	68.97	**65.67**
7. Faculty in the study	67.85	28.33

Table IV displays the percentage of bias reduction attained by the PSA method in estimating the target variable for the web panel sample calculated by equation (4). The PSA's study has utilized seven weighting models to evaluate the reduction ratio of bias in the target variable. The findings suggest that the reduction ratio of bias is 100% in general, with a proportion of 28.57% for considerable bias reduction (i.e., bias reduction exceeding 50%) (Schonlau, van Soest, and Kapteyn, 2007). Model-1 exhibited a 62.33% reduction in bias, while model-4 demonstrated a 34.67% reduction and model-6 yielded a 65.67% reduction. Hence, it is recommended to utilize the estimates derived from weighting model-1 and model-6 in order to calculate the estimates for web panel surveys. According to Schonlau, van Soest, & Kapteyn (2007), the PSA methodology notes that approximately 24.2% of the total twenty-four estimates exhibit a bias reduction of over 50%, which is considered reasonable.

5. Conclusion

In recent times, web surveys have gained popularity due to their appealing attributes in the realm of data collection. Nevertheless, web surveys that rely on nonprobability sampling methods give rise to biases, namely, in terms of coverage, self-selection, and nonresponse. Extensive study has been conducted on web surveys, particularly web panel surveys, in order to tackle the aforementioned challenges and offer potential remedies. The objective of this study is to evaluate the effectiveness of the PSA technique in mitigating bias within web panel surveys. This research endeavor employed a web panel survey to examine the utilization of social networking sites (SNSs) within the educational framework among students enrolled at IIUC. The study gathered data from a sample of 1,920 individuals and analyzed several demographic and background variables, such as gender, age, area, employment status, marital status, program level, and faculty affiliation. The research utilized PSA as a method to address any bias in the findings obtained from the web panel survey. The PSA models exhibited different levels of bias reduction, with Model-1 (gender-based) and Model-6 (program level-based) displaying the most significant reductions in bias, at 62.33% and 65.67% respectively. These reductions in bias are noteworthy, as they exceed the threshold of 50% for considerable bias reduction. The results of this study indicate that by using PSA to account for demographic and background characteristics, it is possible to reduce biases and improve the precision of estimates in web panel surveys. Furthermore, the utilization of the PSA not only resulted in the mitigation of bias but also yielded a reduction in the standard error of the estimation. It is recommended that the PSA technique is an effective tool for reducing bias and improving the precision of the web panel survey results.

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