COMPARING THE WEIGHTING ADJUSTMENT TECHNIQUES FOR REDUCING BIAS IN VOLUNTEER PANEL WEB SURVEYS

PhD Thesis

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Anadolu University, Graduate School of Sciences
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ABSTRACT

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Web surveys have become one of the most widely utilized and popular survey methods in recent years. A web survey is performed over the World Wide Web by inviting individuals to complete the questionnaire by themselves. Internet usage has increased among inhabitants of developed countries as well as developing countries. Since the advent of the smartphone, web surveys have become even more viable and reasonable data collection method. Although, in the last years, internet-based data had been collected only for marketing researches. Data collection on the internet is faster than other methods such as paper-and-pencil, computer-assisted telephone interviews and personal interviews, because it is simple, cheap and provides quick access to the desired large group of respondents. However, in web surveys, bias may arise mainly due to limited coverage and self-selection.

This study appraises characteristics of web surveys, their importance and trend, as well as problems to identify their bias. Some weighting adjustment techniques for reducing the bias are illustrated, and non-probability estimates from volunteer panel web surveys are compared to random sample estimates. Post-stratification weighting, generalized regression modeling, raking ratio estimation and propensity score adjustment techniques are used for reducing these biases. In the application of this study, population estimates are compared to those from a volunteer panel web survey. The data are from the survey *"Using Social Networking Sites in the Education of Students of Open Education System, Anadolu University".* A random sample based on simulation is created by a stratified probability sampling design, and estimates based on this sample are compared with estimates from a non-probability-based volunteer panel web sample. It is shown that the weighting adjustment has reduced the bias substantially and the random sample estimates provide better results than those from the volunteer panel web survey. However, when it is necessary to use volunteer panel web surveys, it is recommended to adjust at least one of the weighting adjustment techniques described in this study.

Keywords: Web surveys; Volunteer panel web surveys; Probability and non-probability sampling design; Random sample; Bias; Weighting adjustment techniques.

ÖZET

GÖNÜLLÜ WEB ANKETLERİNDE YANLILIĞI AZALTMAK İÇİN AĞIRLIKLI DÜZELTME TEKNİKLERİNİN KARŞILAŞTIRILMASI

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Web anketleri son yıllarda en çok kullanılan ve popüler anket yöntemlerinden biri haline gelmiştir. Bir web anketi, World Wide Web üzerinden bireyleri kendi başlarına bir anketi doldurmak üzere davet etmek suretiyle uygulanır. Internet kullanımı, gelişmiş ülke vatandaşları hem de gelişmekte olan ülke vatandaşları arasında artmıştır. Akıllı telefonun ortaya çıkışından bu yana, web anketleri daha geçerli ve makul bir veri toplama yöntemi haline gelmiştir. Son yıllarda, internet tabanlı veriler sadece pazarlama araştırmacıları için toplanmıştır. İnternet üzerinden veri toplamak kağıt-kalem, bilgisayar destekli telefon görüşmeleri ve bireysel görüşme yöntemlerinden daha hızlıdır çünkü basittir, ucuzdur ve arzulanan geniş katılımcı grubuna hızlı erişim sağlar. Ancak web anketlerinde yanlılık genel olarak sınırlı kapsam ve kendi kendine seçim nedeniyle oluşur.

Bu çalışma, web anketlerinin niteliklerini, önemini, eğilimlerini ve de yanlılığı belirlemedeki sorunları değerlendirecektir. Yanlılığı azaltacak bazı ağırlıklı düzeltme teknikleri örnekle açıklanmıştır ve gönüllü web panel anketlerinden elde edilen olasılıklı olmayan tahminler, rasgele örnekleme tahminleriyle karşılaştırılmıştır. Ağırlıklı son tabakalama, genelleştirilmiş regresyon modellemesi, sıralı oran tahmini ve eğilim skoru düzeltme teknikleri bu tür yanlılıkları azaltmak için kullanılmaktadır. Bu çalışmanın uygulamasında, anakütle tahminleri, gönüllü web panel anketi tahminleriyle karşılaştırılmıştır. Veri “Sosyal Ağ Sitelerinin Anadolu Üniversitesi Açık Öğretim Sisteminin Öğrencilerinin Eğitiminde Kullanılması” anketindendir. Simulasyona dayalı rasgele örneklem, tabakalı örnekleme tasarımı ile türetilmiştir ve bu örnekleme dayalı tahminler olasılıklı olmayan gönüllü web panel örnekleminden elde edilen tahminlerle karşılaştırılmıştır. Gösterilmiştir ki ağırlıklı düzeltme, yanlılığı gerçekten azaltmıştır ve rasgele örneklem tahminleri gönüllü web panel anketleri tahminlerinden daha iyi sonuç vermektedir. Ancak, gönüllü panel web anketlerinin kullanılması gerektiğinde, bu çalışmada açıklanan ağırlıklı düzeltme tekniklerinden en az biriyle düzeltme yapmak önerilir.

Anahtar Kelimeler: Web anketi; Olasılıklı ve olasılıklı olmayan örnekleme; Gönüllü web panel anketi; Yanlılık; Ağırlıkllıklı düzeltme teknikleri.

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Md. Musa KHAN

02/03/ 2018

STATEMENT OF COMPLIANCE WITH ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and presentation of my work; that I have cited the sources of all the data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this study has been scanned for plagiarism with "scientific plagiarism detection program" used by Anadolu University, and that "it does not have any plagiarism" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that are involved.

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(Signature)

Md. Musa KHAN

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

WWW	World Wide Web
PAPI	Paper-and Pencil-Interviewing
CAI	Computer-Assisted Interviewing
CAPI	Computer-Assisted Personal Interviewing
CATI	Computer-Assisted Telephone Interviewing
CAWI	Computer-Assisted Web Interviewing
RDD	Random Digit Dialing
IP	Internet Protocol
ID	Identity
SNSs	Social Networking Sites
MAR	Missing at Random
PSA	Propensity Score Adjustment
RB	Relative Bias
MSE	Mean Squared Error
ANOVA	Analysis of Variance

1. INTRODUCTION

The Internet is a tool of data collection. It is usable for conducting web surveys. In web surveys, data are collected from the individuals via the World Wide Web. This method has become more popular. This section consists of rationale and objective of the study, literature review, limitations, and organization of the study.

1.1. Rationale of the Study

The survey research scenario has gone through rapid progress over the last two decades. The first most traditional data collection mode which is paper-and-pencil interviewing (PAPI) was replaced by the computer-assisted interviewing (CAI) method. Now, the most commonly used traditional data collection method comprises of face-to-face surveys (CAPI), computer-assisted telephone surveys (CATI), and mail surveys (CASI, CSAQ) have progressively substituted by web surveys. The online research popularity and acceptance is not surprising. A web survey is an approach to reach a massive number of potential individuals via the World Wide Web. It includes a variety of techniques with diverse aims, target individuals, populations, targets groups etc. Questionnaires can be distributed among large number of individuals at low cost – interviewers or paper-based questioners are not required, and printing and/or mailing costs in the survey is reduced. Web surveys can start very rapidly. It demands less or no time between preparing the questionnaire and starting the fieldwork when compared to traditional studies. These surveys also offer up-to-date facilities, and thus attractive questionnaires can be produced using multimedia contents like pictures, sounds, animations, and movies.

Although web surveys appear to provide a lot more functionalities than traditional types, it is merely another mode or method of data collection. In the web surveys, interviewers are not required. Questionnaire is completed by the individuals over the Internet. However, some problems can make the outcomes of web surveys unreliable. In web surveys, problems which can arise are under-coverage, self-selection, and measurement errors (Bethlehem, 2010). These issues can cause population characteristics (parameter) estimates to be biased. Therefore, wrong decisions can be made on the web survey.

Now, considering the web survey errors, firstly, under-coverage happens if the target population is more extensive than those members having the Internet access. Parameter estimates will be biased if the Internet access individuals do not differ from without Internet access individuals. Secondly, self-selection means that there is a freedom to participate in the web surveys. Individuals are selected by themselves independently in the web surveys. The questionnaire of the study is just put on the web page or websites. Internet accessing respondents visit the website or web page and decide to participate in the surveys. These participants vary significantly from the nonparticipants. Finally, measurement errors are the difference between a measured quantity and its actual value. It involves random error and systematic error. The random error occurs if repeated measurements produce values that may vary around the real value of the quantity. This error may be caused by the limited precision of the instruments used for measuring. It is said to have systematic errors if repeated measurement produces benefits that systematically occur. This may be caused by a miss-calibrated instrument that affects all measures in the survey.

Traditionally population surveys are conducted face-to-face interview mode or by telephone interview (CATI) mode. These surveys must provide accurate and reliable statistics. These types of surveys must have interviewers. Interviewers cooperate the individuals for giving the right answers to the questions. There is no interviewer to assist respondents in the web surveys. Therefore, there is a significant impact, positive or negative, on the quality of data being collected.

Nowadays, it is more stringent to get information from individuals due to an increase in one-person households and dual-income households (Lee, 2011). The interviewers have difficulties in meeting those individuals during daylight hours, and growing concern for privacy is another primary concern involved in the traditional surveys.

The web surveys are feasible because the Internet users have increased among the residents. Internet penetration rate is on an upward trend for developed countries, which aids the use of web surveys that is shown in Table 2.1 and Table 2.2.

Therefore, many national statistical agencies or organizations have started applying web surveys in addition to other survey modes, which use probability sampling methods. These are called “mixed mode” sampling surveys. The web survey in a mixed mode can assist respondents to take part in the survey, but such type of survey still suffers from a decrease in response rate, which may lead to unwanted bias (Lee, 2011). Thus, agencies are exploring alternatives to mixed mode surveys, such as volunteer panel web surveys.

In my opinion, web surveys are less costly and offer a quicker method for data collection. The web surveys are becoming the main data collection method for its advantages. Data collection over web surveys is prone to many errors. Some of these are coverage problem, self-selection problem, and non-response problems. The several weighting techniques can be applied to outweigh the biases.

1.2. Objectives of the Study

Web surveys have recently become more popular because this is an exciting and attractive approach to data collection method. It provides a large group of potential respondents at a low cost to the researchers in a short period of time. However, web surveys have some methodological problems. Specific units in the target populations are underrepresented because of limited Internet access. Furthermore, respondents' enrolment is often done based on self-selection. Though, in web surveys, biases may occur mainly due to limited coverage, non-response, and self-selection. If the objective of the study is to obtain unbiased estimates of population characteristics, the probability sampling design is vital. In this case, self-selection web surveys provide a biased estimate.

This study reveals characteristics and problems of web surveys and helps to estimate more precise estimators. The weighting adjustment techniques may reduce the bias to the under-coverage or self-selection or non-response.

There exist many weighting adjustment techniques. Weighting adjustment is a set of techniques that take an attempt to increase the accuracy of estimates by using auxiliary information. Auxiliary information is defined as a set of variables that are measured in the survey where the population distribution information (or complete survey distribution) is already defined. The response distribution of an auxiliary variable compares with its population distribution. It is assessed whether the sample is representative of the population (concerning this variable) or not. If these distributions differ very less, one may conclude that the sample is selective. Weighting adjustment is calculated for correcting bias. Weights are assigned to all observed elements. Population characteristics estimates are then computed by considering the computed weighted values instead of the unweighted values. Weighting adjustment is often used to correct surveys data that are affected by non-response errors. Weighting adjustment overview was found in Bethlehem (2002) and Sarndal & Lundstrom (2005). There are four weighting adjustment techniques for reducing biases of estimates—post-stratification weighting, propensity score adjustment, generalized regression modeling, and raking ratio estimation.

Post-stratification is a well-known and frequently used method to reduce the variance of the estimates and bias due to non-coverage and non-response. Alongside, propensity score adjustment is used for correcting selection bias due to non-probability sampling whereas generalized regression modeling and raking ratio estimation can be used to correct both non-response and coverage errors that are not controlled by the propensity score adjustment.

Weighting adjustment is required to obtain unbiased estimates of population characteristics when the sample is not selected with equal probabilities. For this reason, the sampling weights must be computed. The aim of this weighting is not reducing or removing the bias but reducing the variance of the estimates. Weighting adjustment technique can be applied to improve the precision of estimates. In addition, it turns weighted sample into representative with respect to some auxiliary variables as well as it is often used to correct the bias caused by non-response errors, coverage errors, and sampling errors.

Therefore, the specific objectives of the study are as follows:

- Studying characteristics and problems of web surveys.
- Finding a more precise estimator of the volunteer panel web surveys.
- Comparing the estimates between probability-based and non-probability-based volunteer panel web surveys.
- Exploring weighting adjustment techniques for reducing the bias in the volunteer panel web surveys.
- Recommending adjustment techniques for reducing bias in the volunteer panel web surveys.

1.3. Literature Review

The survey research has changed rapidly during the last few decades as information and communication technology has developed significantly. The introduction of web surveys for sample data collection has prompted an intense argument about the validness in science (Couper 2000, Fricker and Schonlau 2002, Ilieva et al. 2002, Tingling et al. 2003, & Tuten et al. 2002). Effects in their favor emphasize benefits of cost, fast data collection, efficient result processing, questionnaire design flexibility, and to reach target respondents worldwide.

Web surveys seems to have poor response rates than similar mail surveys (Crawford, Couper, and Lamias, 2001). There are a lot of reasons for lower response rates in the web surveys. One of the reason is lacking effective strategic information for enhancing the response rate. Internet users are getting more and more annoyed with colossal burden of web connections.

Couper (2005) showed that technology trends in survey data collection has been done only using the pencil-and-paper personal interviewing (PAPI) surveys or mail surveys. PAPI surveys are done with interviewers, whereas mail surveys are done as self-interviewing. Along with, increasing the use of telephone in the households led to telephone surveys more famous for survey data collection.

Also, with the increased popularity of computers, computer-assisted personal interviewing (CAPI) has replaced these modes. Interviewers can use computer assisting interviewing instead of paper and pencil interviewing. Moreover, specific software for telephone interviewing has aided telephone surveys to become more convenient and accurate.

Recently, the web surveys have become popular. This survey is done via a web browser in such a way that respondents answer questions by themselves. With increased Internet users, the web surveys have become more viable. Although, problems may arise due to limited coverage and selection problems.

Coverage error occurs when some part of the population cannot be included in the sample, or there are duplicated participants in the list of sampling units or when sampling units in the target population do not belong to the sampling frame. Therefore, survey results are likely to be biased. A web survey sampling frame is formed considering a list of e-mail addresses of the potential members of the target population. Since all the members does not have access to the Internet, and the coverage of the e-mail address of the whole target population does not always exist, all the individuals do not have the equal probability of being selected in the survey. Even though the Internet using rate is growing, the potential bias is not only related to the number of people having the Internet access but also their age, gender, education, and behavioral characteristics' differences (Bandilla et al. 2003, Couper et al. 2007, & Dever et al. 2008). Coverage errors in web surveys can be categorized into the under-coverage or over-coverage groups.

Under-coverage error arises because of individuals not being able to participate in a web survey due to lack of Internet access. Web population comprises of people with the Internet. The potential bias is not only related to the Internet access respondents, but also their age, sex, education, socioeconomic status and behavioral characteristics' differences (Steinmetz et al. (2009). It is well known that young people and those with high levels of education more often have access to the Internet than older citizens and those with low levels of education (Bethlehem, 2010). If some demographic (age, sex, racial origin, education) groups are under-represented, this may cause problems related to bias for inference.

Over-coverage for web surveys may occur when respondents participate multiple times in studies because of incentives. This type of web survey ensues because it is common that respondents have multiple e-mail addresses. Identifying individual respondents in a web survey is difficult. Therefore, there is usually a possibility of the over-coverage problem in a web survey. However, it is often assumed that this problem is less severe.

Another critical problem of probability-based web survey is small sampling frame (Couper, 2000). Like volunteer panel web surveys, non-probability-based methods and self-selection recruitment methods of data collection create problems. Horvitz and Thompson (1952) have shown that estimates of the population characteristics are unbiased if a probability sampling method is being used given that every sampling unit has a non-zero probability of selection, and all these probabilities are known.

Furthermore, the accuracy of estimates can be computed under some conditions. Such a selection does not take place in non-probability-based web surveys. In the web survey process, first, identify the potential respondents then put the questionnaire on the web page (s) or website (s) in order to get the responses of the respondents for the survey. The target population of a self-selected web survey consists of the Internet-connection respondents and having a non-zero probability of visiting the website or web page and participating in the survey. Moreover, a survey research has shown that respondents who were self-selected to a study differ from those who do not have available time, web skills, or selflessness to contribute to the study (Bandilla et al. 2003, Fricker 2008, & Malhotra

& Krosnick, 2007). There is an additional problem of this type of web surveys because all selection probabilities are unknown, it is not possible to compute unbiased estimates for any target population.

Non-response error occurs when respondents in a sample do not provide some required information. Non-response may be a severe problem if answers are significantly different between respondents and non-respondents. The extent of non-response bias depends on both non-response rate and difference between respondents and non-respondents (Steinmetz et al., 2009). When the non-response's reasons are connected to the formed research questions, the non-response error rises with a falling response. Non-response bias is not same as web surveys, but the problem is severe when response rates are lower compared to other models (Lynn, 2008, Kaplowitz et al., 2004, & Shih & Fan, 2008).

The data can be adjusted to remove the coverage errors, non-response errors, and sampling errors. Usually the weighting adjustments techniques give a possible solution to reduce the bias and improve the quality of web surveys (Bethlehem & Stoop 2007, Dever et al., 2008).

Lee and Valliant (2009) showed that using propensity score adjustment with calibration adjustment worked well in their simulation data. Lee (2004) argues, "It becomes the methodologists' responsibility to devise ways to improve web survey statistical methods (e.g., sample selection and estimation) and measurement techniques (e.g., questionnaire design and interface usability)".

Specifically, use of suitable sampling of web surveys is assumed to have a higher likelihood of producing a biased sample (Fricker, 2008). The key problems in web surveys are coverage, self-selection and non-response errors (Bethlehem, 2010; Lee & Valliant, 2009; Fricker, 2008; & Duffy et al., 2005). These problems can occur in volunteer panel web surveys as well. Notably, there is a gap between the total population and the web population. This fact may cause coverage errors. Besides, there are no known selection probabilities during the selecting process from the web population. This effect may cause self-selection error, a kind of sampling error. Finally, there is the possibility of non-response error during the process of getting answers from respondents. These errors may combine to cause severe bias in any quantity that is estimated. Consequently, statistical inference for this kind of survey can be of a doubtful quality.

One of the main objectives of a sample survey is to estimate population characteristics. However, biases mean that the estimated population characteristics are not the same as actual characteristics of the population. Bethlehem (2010) showed that in web surveys, biases arise mainly due to limited coverage and self-selection. Lately, statistical methods have been used to reduce biases in web surveys. A possible solution may be weighting adjustments like post-stratification technique and propensity score weighting procedures. Propensity score weighting uses a widely used tool in epidemiology, the propensity score to compare attributes of web survey respondents to those from a traditional reference survey and apply subsequent adjustments to estimates.

Lee (2011) recommended that “A volunteer panel web survey may be a good alternative so long as the analysis is proper." Lee (2011) used inverse propensity sore adjustment and rim weighting for reducing bias of web surveys.

In the present context of globalization, multi-country and multilingual homogenized surveys are crucial. Arguments against web surveys mostly emphasize on survey errors and for scientific use of survey research, in addition to the related questions of their quality, reliability, and validity. Especially, non-probability-based web surveys have problems because respondents are not selected in the sample randomly. The target population is more suitable than probability-based web surveys. Therefore, to the degree to which the obtained results can be generalized to the population data is very little.

Mainly, *Harris Interactive* which is a commercial polling agency has developed a propensity score weighting technique to correct for attitudinal differences in the data between web surveys and face-to-face surveys. Some researchers have evaluated the weighting procedures for web surveys by comparing them with other survey modes like face-to-face or random digital dialing surveys.

Many web surveys are conducted by non-probability sampling methods like convenience sampling. If a sample is not systematically representative of the population, the resulting estimates of population quantities may be biased. In this case, it is essential to try to minimize the bias.

1.4. Limitations of the Study

There are some limitations in this study. The first limitation is non-probability-based web survey data (volunteer panel web survey) which has been used. Secondly, the auxiliary information of the target population was available, but not the target variable information. A simulation has been performed to obtain the target variable data.

1.5. Organization of the Study

This study consists of five sections. In section 2, the basic concept of web surveys, problems and types of web surveys, advantages and disadvantages of web surveys, sampling design, sources of errors in web surveys, and sampling errors in surveys describes in detail. In section 3, different weighting adjustments techniques for reducing bias in web surveys has been proposed. In section 4, the results and interpretations of the post-stratification weighting, generalized regression modeling, raking ratio estimation and propensity score adjustment techniques have been elucidated. Finally, evaluation of results, some discussion, and conclusion has been shown in section 5.

2. WEB SURVEYS

Surveys are used to collect data on the populations' characteristics. A census can be conducted by observing every unit of the target population. However, a sample survey can provide more valid results in a shorter period at a lower cost—i.e., is relatively more utilized. Although the web survey is a relatively new method of data collection, it has a lot of benefits with a few shortcomings. In this section of the study, the data collection trends, the definition of web surveys, pros and cons of it, problems regarding the web surveys, their sampling design and general scenario, and the total errors of surveys' overview are briefly described in a sequential manner.

2.1. Data Collection Trends

Use of web surveys to extract data from the surveys is a novel step in the development of data collection methods. Collection of data and their compilation to a summary is a very old technique. Even in ancient times, rulers exploited the statistical data for making sophisticated decisions involving the kingdom. And, it is not surprising to see that statistics has had incessant influence on our continuously developing society till the present day.

Until the year 1895, statistical data was being collected on the entire enumeration of populations, also known as census. The primary purposes of these censuses were to count the population size, to fix tax payments to the citizens, and to determine the military capability of the country. There was no idea about sampling nevertheless (Bethlehem & Biffignandi, 2012).

A fundamental change happened in 1895. Population size had increased to enormous numbers. It was entirely the era of industrialization. Centralized governments needed new information about the nation. It was the suitable time for data collection by sample surveys. The very first concepts about sample surveys surfaced around the year 1895. Between the year 1895 and 1934, plenty of discussions occurred about how samples should be collected. These pointed to probability sampling or another sample selection designs (Cochran, 1953).

Survey data collection based on only probability sampling offers valid and correct estimates. By the year 1934, these types of surveys were considered as a scientific method for data collection. A substantial amount of surveys was carried out using probability sampling between the 1940s and the 1970s. The questionnaires were of paper forms. These surveys involved face-to-face, telephone, or mail surveys (Couper, Blair, & Triplett, 1999).

In some places in the 1970s, computer progress had started. The fast microcomputers' development made it attainable to acquaint with computer-assisted interviewing (CAI).

Therefore, survey data collection became fast, less expensive, and more comfortable, and it enriched data quality (Couper, Blair, & Triplett, 1999). The developed methods were abbreviated as CATI (computer-assisted telephone interviewing) and CAPI (computer-assisted personal interviewing) developed.

The next vital development was the Internet connection around the year 1982. Having Internet access to a significant number of people and companies, it became viable to use this network for data collection in the surveys. The e-mail surveys were the first Internet surveys. The World Wide Web (WWW) was acquainted with individuals in 1989. The Internet usage skyrocketed with the development of browsers. The WWW became extensively available and the web surveys progressively substituted the e-mail surveys in the middle of 1990s (Couper et al., 1998).

Web surveys are a significant approach for the data collection of surveys due to their benefits. They allow simple, fast, low-cost interviews of massive groups of potential individuals (Clayton, & Werking, 1998). The number of conducted web surveys have risen over time as expected. However, there are some methodological difficulties also. There are plenty examples of web surveys which are based on non-probability sampling methods. Therefore, the interpretation of survey results in the population is doubtful.

Usually, the data collection of surveys is not simple, cheap or fast. Some continual efforts have been made all through the survey research history to shorten the time and lower the costs while maintaining the data quality. The development of information and communication technology led to the introduction of computer-assisted interviewing (CAI). Paper questionnaire was replaced by an electronic version. In this case, data are collected within a short time and low-cost with a high level of data quality. Couper et al. (1998) said that the CAI approach was beneficial.

Now, web surveys are feasible because the Internet usage has expanded more among the developed countries' citizens. Table 2.1 shows the percentage of world's population using the Internet from the years 2005 to 2017, sorted by market maturity. The

Internet penetration rate is increasing surprisingly over time for developed countries, which aids the use of web surveys. Now, the world Internet access rate is 48%. In 2017, the Internet penetration rate is 81% while it was 51.30% in 2005. In the year 2017, the people who lived in the developed countries, their internet usage rate (81%) is doubled compared to the developing countries' individuals (41.3%). Developed countries have a greater support web surveys for data collection.

Table 2.1. *Percentage of individuals using the Internet of world population from 2005 to 2017 (www.statista.com)*

Year	Developed countries (%)	Developing countries (%)	World (%)
2005	51.30	7.70	15.80
2006	53,50	9.30	17.60
2007	59.10	11.80	20.50
2008	61.30	14.50	23.10
2009	62.90	17.20	25.50
2010	66.50	20.60	28.90
2011	67.7	23.40	31.30
2012	72.00	26.30	34.30
2013	73.80	29.00	36.90
2014	75.60	32.40	39.90
2015	77.40	36.10	43.20
2016	79.60	39.00	45.90
2017	81.00	41.30	48.00

Table 2.2 compares the Internet users in the world by regions. Internet penetration is the largest (88.10%) in North America. The Internet access is more than 80% in Europe. On the other hand, there are two regions where the Internet penetration rate is less than 50%. The lowest percentage of Internet-using rate (31.20%) is in Africa. The average Internet using rate in the globe is 51.70%.

Table 2.2. *Internet users in the world by regions, June 30, 2017 (www.internetworldstats.com)*

World regions	Penetration rate (%)
Africa	**31.20**
Asia	46.70
Europe	**80.20**
Latin America/Caribbean	62.40
Middle East	58.70
North America	**88.10**
Oceania/ Australia	69.60
Average	**51.70**

2.2. Definition of Web Surveys

The Internet is a tool for data collection that offers for carrying out surveys of respondents with Internet access. Web surveys collect data via a web browser in such a way that respondents answer questions about the electronic questionnaire by themselves. The questionnaire accesses by means that of a link to a web page. Web surveys have become more viable because the usage of the Internet among developed countries' citizens has expanded (Crawford, Couper, and Lamias. 2001). It is a comparatively new methodology. It is a desirable method of data collection with high quality by considering a short period at a low cost (Couper, 2005). Hence, the web surveys have grown very quickly, but the web surveys methodology has not developed at a similar rate yet. This problem will be overcome when web surveys are sound and have a scientifically valid theory. Therefore, the statistical research described has a crucial future importance. Web surveys have become a necessary research tool for a spread of research fields, together with marketing, social, and official statistics research (Tourangeau, Conrad, & Couper, 2013).

There are three modes of traditional data collection and their linkage to the web surveys are discussed below:

- **Mail interviewing or Questionnaire or Paper forms:** Questionnaire/Paper forms send to respondents (e.g., by mail, fax, or dropped off) for respondents to self-complete and return.
- **By telephone:** It is a mode of data collection where interviewers connect with the phone to selected respondents and interview over the telephone and ask

questions and record the answers on the paper questionnaire form or a computer program for computer-assisted interviewing (CATI, computer-assisted telephone interviewing).

- **Face-to-face:** The interviewers meet the selected respondents in the sample and record the answers on the paper questionnaire form by asking questions or a computer program for computer-assisted interviewing (CAPI, computer-assisted personal interviewing) (Tourangeau, Conrad, Couper, 2013).

Web surveys are like mail surveys. Both data collection modes work by using visual information transference, but the telephone interviewing and face-to-face interviewing modes utilize oral data transference. In web surveys, interviewers are not required for data collection. Data collection is done by self-administered interviews.

Of course, web surveys are a computer-assisted type of data collections like CAPI and CATI. Therefore, it is also referred to as computer-assisted web interviewing (CAWI). The features of mail surveys are different from web surveys. Questionnaire forms of web surveys are an electronic format which routes automatically all through questionnaire and checks automatically for anomalies (Schonlau et al., 2002).

2.3. Problems in Web Surveys

Web surveys may suffer from coverage, self-selection, and non-response problems. These problems have briefly described below:

2.3.1. Coverage problems

Coverage problems may occur in the web surveys. It happens if all the sampling units in the population have no Internet access or sampling units consist of duplicate participants. Only individuals who have the Internet access will be selected in the sample. The estimates of population characteristics may be biased because of the coverage problem. It can lead the web surveys being under-coverage or over-coverage.

The more common problem in web surveys is under-coverage. Respondents who have no access to the Internet cannot join in a web survey. Only the Internet access individuals cover the target population. Steinmetz et al. (2009) showed that the possible bias is associated not only with the Internet access people, but also their demographic characteristics' differences. Bethlehem (2010) remarks that highly educated young people have more Internet access than older adults having low levels of education. Underrepresented demographic groups can cause bias problems for decision making.

Unlike web surveys, computer-assisted telephone (CATI) survey can suffer from this coverage problem. In this study, sampling frame consists of telephone directories. This problem occurs because people have no phones or people having unlisted numbers will not be included in the survey. Surveys not offered on cell phones may worsen this problem. The usage of the Internet is increasing rapidly not only in developed countries but also over the globe. So, web surveys' under-coverage problems may decline soon. Web survey may also suffer from the over-coverage problem (Cobben, & Bethlehem, 2005). It may occur if people participate multiple times in web surveys for incentives. It is not easy to identify individual respondents in a web survey because people have multiple e-mail addresses. Though, it is considered that this problem is negligible.

Some approaches can assist to reduce the bias from under-coverage problem. The first step is to offer Internet facilities to people in the sample having no Internet access. This approach may not fully resolve the problem as they might not be interested in working with the Internet. Secondly, a mixed-mode survey is another approach. Face-to-face or computer-assisted interviewing or mail modes of data collection can utilize for having no Internet access. The third step is to apply some adjustment weighting techniques which has been discussed in section three. The under or overrepresented strata correct bias using weights. There is no assurance that the weighting adjustment will eliminate the bias of the estimate.

2.3.2. Selection problems

Non-probability sampling designs, specially convenience sampling, are prevailing in web surveys because it is inexpensive and less time consuming. This fact creates sampling error which was discussed in types of error section earlier.

Horvitz and Thompson (1952) illustrated that when probability sampling design is used, and every sampling unit selection has a non-zero probability and knowing these probabilities, the researchers can calculate the unbiased estimates under these conditions and the precision of estimates as well. Though, self-selection webs surveys do not fulfill these requirements.

Usually, people who do not have ample time, web skills or inclination to contribute to the survey can differ from self-selected people into a survey (Steinmetz et al., 2009).

In other words, volunteer web surveys' participants may have desired features. Thus, its response may differ from a randomly selected response in the population.

Loosveldt and Sonck (2008) acquainted with some previous research to learn this selection bias – self-selection web surveys were compared with the computer-assisted telephone surveys or face-to-face surveys. Firstly, web volunteer panel surveys were compared with the probability based face-to-face surveys (Duffy et al. 2005). They explored that respondents of web survey were more active in social politics than a face-to-face survey. Bandilla et al. (2003) also found significant differences between the Internet using respondents and mail survey respondents where self-interviewing performed. Even though an adjustment is worked out to the Internet access people for essential socio-demographic characteristics, there was no change in the difference between them. Bethlehem (2010) showed that volunteer web surveys by self-selection in samplings are biased estimators theoretically but may have unbiased estimators practically. Therefore, for the valid decision, it must have stiff structural assumptions (Lee, 2004). The survey researcher has no control over the self-selection because of their selection probabilities are not known. Several approaches can assist to reduce self-selection bias. Firstly, we may choose a proper sample by probability sampling design. The second attempt is to implement suggested weighting adjustment techniques. By using weights, the response is adjusted for under or overrepresented strata in the sample.

2.3.3. Non-response problems

Non-response error happens when selected members in a sample do not deliver some essential information. If answers of the respondents differ from non-respondents significantly, non-response may pose a severe problem. Steinmetz et al. (2009) showed that the degree of non-response bias relies on both non-response proportion and difference between non-respondents and respondents in the sample.

This bias varies in web surveys. However, the web surveys response rate is lower than other modes of data collection. Lozar et al. (2008) explored that, in web mode, non-response rate is on an average 11% lower than other methods. Efforts (follow-up contacts, incentives), technical troubles (slow, low-end browsers, unreliable connections), personal computer accessibility, and privacy and confidentiality concerns are reasons for a low response rate of web mode (Steinmetz et al., 2009). As selection probabilities of elements in volunteer panel web survey are not known, so that exact non-response rate is not possible to compute. Nevertheless, non-response bias may be a severe problem in web surveys. Detection of non-response is difficult. In this study, missing at random (MAR) is assumed to be non-response. The application of removing non-response has been discussed in section three.

2.4. Advantages and Disadvantages of Web Surveys

Duffy et al., (2005) and Bethlehem (2010) outlined the advantages and disadvantages of web surveys shortly. The principal benefits of web surveys are low cost and speed. It takes the limited cost to distribute questionnaires and no cost in mailing, printing, and data entry. Additionally, no interviewers are required so, interviewer effects can be avoided. Surveys can be launched and data from respondents can be obtained very quickly. This mode allows the utilization of a lot of visual, flexible and interactive technologies like sound, pictures, animation, and movies. Finally, web surveys can do at respondent's convenience, which implies that individuals who could not have been reached by interviewers throughout the day can fill questionnaires whenever they like.

However, there are some drawbacks to web surveys. The disadvantages focus mainly on sampling problems under-coverage and self-selection problems. In addition, restricted sampling designs and availability of respondent also a severe problem for the web surveys. The restricted populations are less probable to access the Internet and reply to the web questionnaires. A probability sample selection is complicated based on visiting websites or e-mail addresses. Though, the response rates of online surveys in several fields are equal to or slightly more than that of traditional modes of data collection. The Internet users, nowadays, are perpetually blitzed by messages and can merely erase your advances. No interviewers are needed in these surveys. Scarcity of a skilled interviewer to explain and probe can probably lead to less reliable data as well online hacking may cause for data manipulation by hackers which can mislead to results of the web surveys.

2.5. Approaches to Web Surveys

In web surveys, firstly, surveys administrator must contact the potential respondents and invite to participate in the web surveys. In general, the subsequent steps are probable:

- Survey administrator sends an e-mail with a link to the website comprising the survey questionnaire to the desired individuals. The link has a unique indication code. The distinct code guarantees that an individual can answer the questionnaire only one time. It also confirms that only selected people are to answer the questionnaire.

- Select desired respondents when they are visiting a website. Invited participants start the survey by clicking on a link or button. They may be required to enter a typical website having the survey questionnaire, or pop-up window screen showing the questionnaire for starting the survey.
- This step is a very simple way to run a web surveys. In this case, there is no need to send e-mails or letters to the participants. However, it has a drawback that proper sampling design is not applied. It may cause deficiencies of response representativeness. There is a possibility to participate the surveys more than once. Moreover, every respondent may not be a member of the target population. Technical problems may stop opening the survey (Bethlehem and Biffiganandi, 2012).

The questionnaire of a web survey may have one or more web pages. Participants visit this website or web page to participate the survey. The empty questionnaire is sent to the respondents via Internet and completed answered questionnaire back to the survey agency.

2.6. Types of Web Surveys

Internet surveys and web surveys are sometimes used interchangeably. However, strictly speaking, both are different concepts. Web surveys are done only on web browsers via the Internet, whereas Internet surveys are a collective term for several procedures of data collection via Internet. Internet surveys include both web surveys and e-mail surveys which are done by e-mail. Sampling methods can be divided into probability sampling and non-probability sampling. Type of web surveys can also be categorized based on both sampling methods. Table 2.3 which is a version of Couper (2000), shows the classification of types of web surveys based on availability of probability sampling and non-probability sampling. Couper (2000), Lee (2004) and Fricker (2008) describe the characteristics of these kinds of web surveys, which are summarized below:

Table 2.3. *Types of web surveys*

Non-probability	**Probability**
i. Entertainment polls ii. Unrestricted self-selected surveys iii. Volunteer panel surveys	iv. Intercept surveys v. List-based sample surveys vi. Pre-recruited panel surveys vii. Web option in mixed mode surveys

2.6.1. Non-probability web surveys

Web surveys using non-probability sampling methods comprise entertainment polls, unrestricted self-selected surveys and volunteer panel surveys. The non-probability-based web surveys are problematic because of not having an equal probability of being selected.

2.6.1.1. *Entertainment polls*

Firstly, entertainment polls may not be considered a scientific survey in a sense, but they are very trendy in many websites. Polls make no claims regarding representativeness. Respondents are typically volunteers. They mostly work for entertainment purposes. They make of websites where any visitor/respondent can reply to forwarded surveys. There is no control over who responds. For example, CNN Quick vote (www.cnn.com) polls for entertainment (Tourangeau, Conrad, Couper, 2013)

2.6.1.2. *Unrestricted self-selected surveys*

Unrestricted self-selected surveys are open for anyone to participate in it. There are no restrictions on participants. Couper (2000) inserted some examples of this type of web survey. One is: National Geographic Society's "Survey 2000" which set up in 1988. An invitation to the study put on its website, and the URL was available in its magazine. Over 50,000 respondents completed the study. In the results of the survey analysis, they mentioned that the survey did not conduct a probability sampling method and the probabilities of selection in the sample are not known. They estimated the selection probabilities and compared the distributions of typical demographic variables to official government statistics and applied weighting. However, Couper (2000) indicated that, despite the large sample size, the respondents of the surveys might not to be like the U.S. population on many vital determinants due to self-selection bias.

Berson et al. (2002) conducted a web survey titled “to better understand the risks to adolescent girls online". It is another example of the web survey. Over 10,000 responses pulled in. Unlike the first example, the authors were cautious to properly illustrate their results: “The results highlighted in this paper are intended to explore the relevant issues and lay the groundwork for future research on youth in cyberspace. It is considered an exploratory study which introduces the issues and will need to supplement with ongoing research on specific characteristics of risk and prevention intervention. Furthermore, the generalizability of the study results to the larger population of adolescent girls needs to consider. Due to anonymity of the respondents, one of the limitations of the research design is the possibility that the survey respondents did not represent the experience of all adolescent girls or that the responses exaggerated or misrepresented.”

Those kinds of surveys’ results cannot be generalized to a greater population because researchers do not have any control over the respondent’s participation mechanism (Lee, 2004). However, it does not mean that those type of surveys are inappropriate. Those kinds of surveys can be supportive in recognizing relevant issues for future probability-based surveys (Berson et al., 2002). Furthermore, Fricker (2008) indicates that those kinds of surveys have a benefit in that they are accessible to people who are hard to outreach as they are rigid to recognize or locate or may exist in such slight values that non-probability-based sampling would be possible to reach them, inadequate individuals.

2.6.1.3. *Volunteer panel web surveys*

Volunteer panel web surveys are conducted based on panelists which consist of individuals who decide to participate voluntarily in surveys via websites. Before surveys, necessary demographic information of members is collected from those volunteers when they sign up for the registration. Then, based on the registered member’s database of the potential respondents, researchers can select panel members for a survey using sampling methods like probability sampling or quota sampling methods according to the volunteers' demographic information (Tourangeau, Conrad, & Couper, 2013). In this survey, respondents take part in various surveys as members of web panel. However, it is mentionable that the first group of volunteers is self-selected sample. Couper (2000) illustrated that this type of web survey had received much attention within web survey industry recently. *Harris Poll Online* is a familiar illustration. Harris Interactive says on its Website: “The Harris Poll Online Panel consists of individuals from throughout North America, and Western Europe who have double opted-in and voluntarily agreed to participate in our various online research studies. Through our careful recruitment, management and incentivized panel members, we are confident that we have one of the highest quality panels anywhere in the world with sufficient capacity to provide our clients with the feedback they need to make sound and compelling business decisions. Top quality panels coupled with deep profiling of our members allows us to target and accurately survey certain low-incidence, hard-to-find subjects, rapidly survey large numbers of the general population, and conduct a broad range of studies across a wide array of industries and subject-matter sets."

In this type of surveys, incentives are often offered to panel members to encourage joining in the surveys. Harris Interactive also provides rewards for their panels. For the survey, they use the vital approach to analyze the propensity score adjustment for bias reduction, which has described in section three. Couper (2000) argued that there are two conditions to achieve probability-based web samples such as limited web access, and no data exist of the complete sampling frame of Internet users. One is to limit the population of interest so that the sample restricts to the web users. The other is to utilize alternate methods such as RDD at the same time to recognize and reach a more significant sample of the population.

2.6.2. Probability-based web surveys

In contrast, probability-based web surveys are possible when there is a proper sampling frame that permits to collect a probability-based sample from a population in which each respondent has an identical probability of being included in the sample. Probability-based web survey types include: intercept surveys, list-based sample surveys, pre-recruited panel surveys, and web option in mixed mode. For probability-based web survey, all elements of the target population are well-known. Such type of data can merely be analyzed by exploiting the ideal inference approaches, and it permits the generalization of results across the target population (Tourangeau, Conrad, Couper, 2013).

2.6.2.1. *Intercept surveys*

Intercept surveys are pop-up surveys taking place on a specific website that use systematic sampling methods or random sampling. In systematic sampling method, researchers invite every k^{th} visitor to the site to visit the survey website. In this case, the target population is defined as visitors to the website so that this sampling allows generalization the population. Internet Protocol (IP) addresses can be used to control multiple submissions answers from the same computer user. These surveys are very advantageous as customer-satisfaction surveys or site evaluations, but the problem with this type of survey is non-response (Couper, 2000 & Fricker, 2008). Low response rate can arise from non-response bias and there may be no way to assess it because those who complete the surveys may have diverse opinions compared to those who ignore the invitation.

2.6.2.2. *List-based surveys*

This type of probability-based web survey is a list-based sample survey. The approach of this type of survey starts with a sampling frame or list of those members with web access. Not all Internet users can enter the specific websites. That is, the population control to the web users. Therefore, this type is useful for intra-organizational surveys like student surveys, government organization surveys, and extensive corporation surveys. In this case, there is little chance of coverage problems. Couper (2000) said that this survey is “list-based samples of high-coverage populations.” E-mail or ID number is usually used to invite participation in the surveys. To invite the respondents simple random sampling is straightforward. To implement more difficult sampling methods such as a stratified sampling or cluster sampling more auxiliary information is required.

2.6.2.3. *Pre-recruited panel surveys*

Third, pre-recruited panel surveys are like volunteer web panel surveys in the logic of that panels comprises of members who have agreed to join in surveys. The critical difference is that the pre-recruited panel surveys use probability sampling methods such as RDD for recruiting panels, while the volunteer web panel surveys do not use probability sampling methods (Tourangeau, Conrad, & Couper, 2013). Researchers enlist panel members via telephone or postal mail rather than web or e-mail. After getting information from those panel members, sub-samples can be drawn as the researchers' desire. Since, the population is controlled by the web users, then there is again little chance of coverage errors. In this case, the population includes individuals with no web access, equipment, and web access consider for corresponding panelists.

2.6.2.4. *Web option in mixed-mode surveys*

A final use of web surveys is as an alternative mode in mixed-mode surveys. Participants in the surveys are selected by a probability sampling method and are given a choice to complete the study using one of several ways of data collection, such as Web, telephone, mail, or face-to-face. The same survey is offered in each mode. The use of web mode signifies a reduce cost to the agency and in burden to the respondents. That is why many national statistical offices (e.g., Europe, Canada, USA, Korea) have utilized this kind of web survey, as mentioned above. There is slight chance of coverage errors or sampling errors in mixed-mode surveys. Mode effects can be an issue in this case, but it is often assumed that they are ignorable nevertheless. Lee (2004) claimed that design-based statistical inferences can be drawn only under these above mentioned four probability-based web surveys.

2.7. Typical Web Surveys Scenario

In this section, distinctive circumstances determine in which a web survey can be conducted. These things identify various essential features that result in several survey cases (Callegaro, Manfreda, & Vehovar, 2015).

Target population: General population surveys, people or households are target population. In business surveys, company staffs, company customers and so on are target population.

Survey administrator: Survey administrator means whose organizes the surveys. An official statistical government body, commercial market research company, university, or another research institute can be a survey administrator.

Cross-sectional versus longitudinal data collection: A web survey that collects a sample from the desired population at one point in time is called cross-sectional web survey. The purpose of the web survey is to illustrate the condition of the target population at that moment in time whereas a web survey that collects the similar sample from the desired population at several points in time is known as longitudinal web survey or web panel. The purpose of this survey is to illustrate the variations of the target population over time.

Technical implementation: The design of the questionnaire prepares on the www which is as a website or web page. In this situation, the questionnaire fills up online. The Internet acts as a medium for respondents. For example, an attachment of questionnaire in an excel spreadsheet sends to an e-mail address of respondent. In this condition, the questionnaire is filled up off-line. It is an e-mail survey example. For execution of the questionnaire, there are two feasible approaches: online data collection and off-line data collection (Callegaro, Manfreda, & Vehovar, 2015):

On-line data collection: On-line data collection is a method of data collection that the participants need to stay online throughout the procedure of responding the questions. The questionnaire is employed jointly on a web page or web pages. The participants must surf on the website carrying the survey to begin answering the questionnaire. The questionnaire may be question-based, or paper form based. In the case of question-based questionnaire, one question covers in each web page. When a respondent replies one question, the respondent heads to succeeding page.

Off-line data collection: The electronic version of questionnaire form distributes to the individuals by e-mail, or it can download from the Internet. The respondent completes it off-line. It is sent back to the survey administrator by finishing the questionnaire.

2.8. Area of Application of Web Surveys

Web surveys can be utilized in any field of the implementation given that the individuals within the population have access to the Internet and they must have some computer skills. Some individuals have no computer can receive one (with access to the Internet), along with simple directions to be used. This solution is for general population web panels. If the data collection by web survey is feasible for all desired individuals, a web survey can be an advantageous tool for data collection which will minimize cost and time and high-quality data as well.

Unfortunately, all individuals in the target population have no access to the Internet, elementary computer knowledge or sufficient questionnaires processing power. It may true for general-population surveys as well as other feasible desired population. Even though the usage of the Internet is increasing, there are differences between developed and developing countries and groups of populations. There are massive changes in computer equipment, technical expertise, and screen settings which create the problems. Thus, for conducting an effective web survey, it is required a statistical procedure which is efficient and reduce a probable bias of the estimate. And if it is not possible to avoid a bias, weighting adjustments methods can be applied to remove this bias (Tourangeau, Conrad, Couper, 2013).

In application, despite the procedural challenges, many surveys particularly commercial surveys are organized on the web. These are suffering from reliability of the results and coverage problems or elementary computer knowledge. Such surveys are run entirely on the web and thus, these meet only one portion of the aim. When the results of a web survey are used, one should bear in mind of possible problems. Therefore, the web survey quality determines by evaluating the procedural explanation in the evidence.

2.9. Sampling for Web Surveys

In web surveys, data are collected via the web browsers. The objective of web surveys is to study a well-defined population. Such target population may be individuals, households, or companies. If a survey is conducted, that information is gathered by asking questions to the representative individuals in the population. To meet the objective of the web surveys a reliable approach is employed in the questionnaire. The technique of selecting a sample from the representative population is called sampling and when it applies for web surveys is known as sampling for web surveys. There is a one way to collect data about target population considering all its elements. Such an investigation is called census or complete enumeration. This procedure has some demerits. It is expensive, more time consuming, and less efficient.

Large-scale investigations raise the response problem (Callegaro, Manfreda, & Vehovar, 2015). As many people are to participate, they must know about it which is a burden. Therefore, they will not be more interested to cooperate.

A sample is a representative subset of a population. A survey collects data from the target population. Only sampled units give information about the sample. Non-sampled elements of the population will not provide information about the sample. If the sample is obtained by the scientific sampling design, it helps to make inference regarding the population. Scientific sampling design means that the sample is selected by applying probability sampling method (Tourangeau, Conrad, & Couper, 2013). If it is comprehensible about how the sample selection procedure works, and the probabilities of each sampling unit selection in the sample is computable, reliable and accurate conclusions can be obtained regarding the population. Since the 1940s, the probability sampling design principles are efficiently functioned in education and official statistics as well as in commercial market research.

2.9.1. Target population

The first phase of a web survey is to define the target population. This population can be observed and come at decision. Suppose, the study wants to know the information about use of social networking sites in the education of Open Education System students at Anadolu University. Here, all students of Open Education System at Anadolu University are the target population. The target population definition should be clear and comprehensible.

Each non-success to incorporate related parts in the population, and not to include digressive ones, might affect on the survey results (Bethlehem, Biffignandi, 2012).

Let U be the finite target population and N is known. It is mentionable that this is not for all case. For examples, the number of individuals having Internet access or the quantity of foreign visitors of a country. The target population elements should be distinguishable. It suggests that these will unambiguously be allotted order numbers $1, 2 \ldots, N$. The notation of target population is, $U = \{1, 2, \ldots, N\}$.

2.9.2. Target variable

The purpose of the planned survey design must illustrate into real functioning approaches. The definition of the target variables of the survey includes in it. These variables quantify the several features of the phenomena to examine.

Let Y be a target variable. The values in the target population U denote by $Y_1, Y_2, \ldots, Y_N$. Target variable may be more than one.

Usually, in the survey, lot of variables are evaluated, and these term as auxiliary variables. These variables facilitate in distinguishing the survey outcomes for several sub-sets of the populations. These sub-populations can assist to precise estimates of the target population characteristics.

For example, demographic characteristics like gender, age, region, working status, and marital status, etc. Let us suppose that X be an auxiliary variable. For the population U, X variable values specify by $X_1, X_2, ..., X_N$.

Both target variable(s) and auxiliary variable(s) can be one of following types:

- **Continuous variables:** The value differs with a limit. These variables count quantities. It is possible to execute expressive calculations on these quantities, i.e., calculating total and average of the target variable(s). Income, expenditure, and height of a person, etc. are example of continuous variables
- **Categorical variables:** These variables split the target population into strata. The value varies according to attribute. It denotes labels of categories. It is not significant to execute calculations on categorical variable values. Examples of categorical variables are gender, religion, marital status, and education level, etc. are categorical variables' examples.
- **Indicator variables:** This variable measure whether an individual has a certain property. It takes value 0 and 1. The value 1 indicates that an individual has the feature, and the value 0 means that the individual has no that property (Groves, et al., 2009). For example, an indicator variable is *"using social networking site in the education"*. If a student uses social networking sites in the education, the variable value is 1, and otherwise, it is 0.

2.9.3. Sampling frame

Probability sampling design and sampling frame are two essential components for selecting sample from a target population scientifically. A sampling frame consists of all identifiable elements in the target population. For connection to the elements, there must be contact information available. Name and address, a telephone number, or an e-mail address, or national ID number can be contained in the contact information. The complete list of e-mail addresses of all elements of the target population can be used as an ideal sampling frame for a web survey. An e-mail address is identified the elements of the target population. A sample can be taken from the population. Survey administrator sends an e-mail to all desired elements which contain a website or web page link having the survey questionnaire.

In sampling frame, two problems might occur such as under-coverage and over-coverage problem (Bethlehem, Cobben, & Schouten, 2011). In Under-coverage, it happens if the sampling frame is not representative to the target population. Such elements can exclude from the sample.

Over-coverage problem is the second problem of sampling frame. In this case, elements of sampling frame occur more than one to the target population. If data collects such type of sampling frame, population parameter estimates will be biased. Figure 3.1 illustrates the target population, and sampling frame with under-coverage and over-coverage problems.

Let a web survey executes with the residents of a district. If e-mail addresses of the inhabitants are not available, it sets a decision to select individuals by telephone. A residents' sample collects from the town telephone directory. The coverage problem is serious which occurs from such sampling frame.

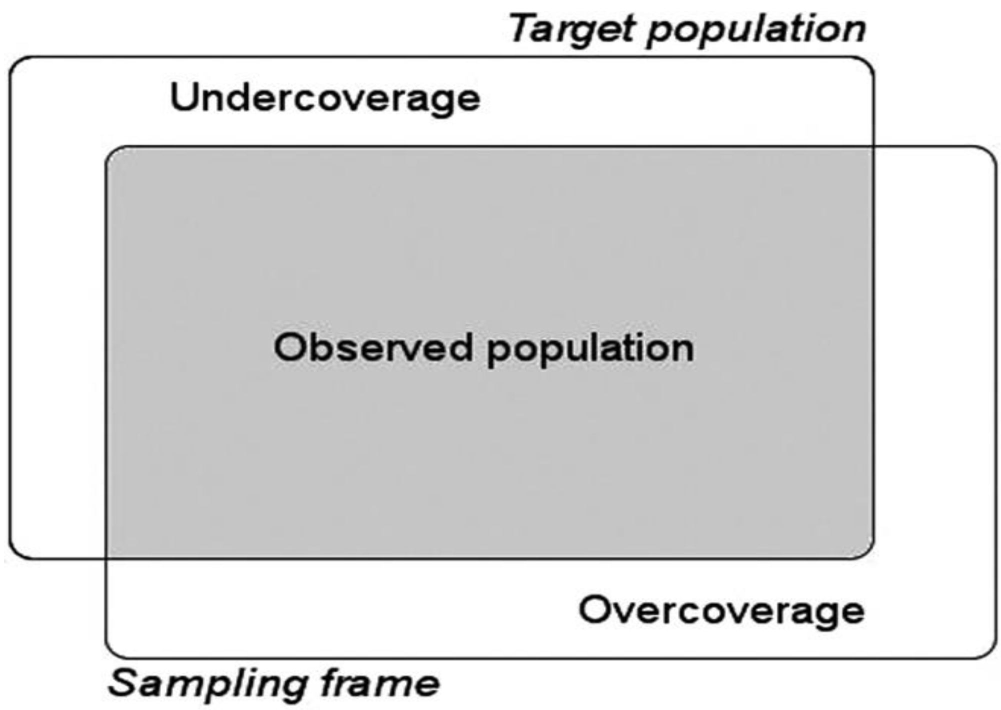

Figure 2.1. *Target population and sampling frame (Bethlehem,2012)*

2.9.4. Determining the sample size

The important thing of sampling design is to determine the sufficient sample size. If the sample size is higher than the required sample, time and cost will increase. On the contrary, if the sample size is too small, a precise estimation cannot be obtained, and survey results will be less efficient. There is a strong positive association between the sample size and the precision of estimates. If sample size is large, the estimates will be more correct (Groves et al., 2009). The precision of an estimates is determined once the size of the sample can be calculated. Large sample indicates a highly precise estimate. Per interview, the cost makes a survey expensive. If e-mail addresses are available and electric version of questionnaire is prepared at once, the survey will be very cheap. Simple random sample (without replacement) size determining formula is given below:

2.9.4.1. *The sample size determination for estimating a percentage*

Before determining the sample size, the researcher is provided with some hint about the margin of error. The margin of error explains as the difference between the parameter estimate and the lower or upper bound of the confidence interval (Cochran, 1953). The effective sample size formulas are given according to margin of error.

For 95% confidence interval, the margin of error is expressed as

$$1.96 \times S\ (p) \tag{2.1}$$

If confidence interval is 99%, the 1.96 value will be replaced by 1.65.

Let the maximum value of margin of error be *M*. This can write as

$$S(p) \leq \frac{M}{1.96} \tag{2.2}$$

In the case of population percentage, the variance of the estimator which turns to the condition

$$\sqrt{\frac{1-f}{n}\frac{N}{N-1}P(1-P)} \leq \frac{M}{1.96} \tag{2.3}$$

where *P* is population percentage. The lower bound of the sample size can be obtained by solving (2.3) equality (Cochran, 1953). It can solve this problem as

- *P* value can be estimated from previous surveys. It can be solved by substituting in the expression (2.3).
- *P* values is unknown. Solving the inequality (2.3) which tends to a lower bound of *n* equal to

$$n \geq \frac{1}{\frac{N-1}{N}\left(\frac{M}{1.96}\right)2\,\frac{1}{P(1-P)+\frac{1}{N}}} \tag{2.4}$$

If population size N is very large, a simple approximation obtains. This indicates that equation (2.4) turns to

$$n \geq (\frac{1.96}{M})^2 P(1-P) \tag{2.5}$$

2.9.4.2. *The sample size determination for estimating a mean*

For sample mean, inequality (2.2) can be revised as

$$\sqrt{\left(\frac{1}{n}-\frac{1}{N}\right)S^2} \leq \frac{M}{1.96} \tag{2.6}$$

where, S^2 is the adjusted population variance.

In this case, the approximate value can be put in equation (2.5). Revising the expression tends to

$$n \geq \frac{1}{\left(\frac{M}{1.96S}\right)^2+\frac{1}{N}} \tag{2.7}$$

If N is very large, then *1/N* tends to zero. It yields the slightly simple form (Cochran, 1953)

$$n \geq \left(\frac{1.96S}{M}\right)^2 \tag{2.8}$$

2.9.5. Sampling designs

If a sample is selected by probability sampling method, a reliable and more precise estimator is obtained. Sampling designs can be categorized into two: probability sampling design and non-probability sampling design. In probability sampling, each sampling unit is selected in the sample from the target population which has a specific probability, but non-probability sample are selected based on the personal judgment of the researchers. Probability sample gives a more precise estimate. Another sampling design is mixed sampling. In this sampling, some elements select by probability sampling, and non-probability sampling selects the remaining items. A brief discussion about some important probability, and non-probability sampling designs has been given below:

2.9.5.1. *Simple random sampling*

The very familiar and possibly frequently used sampling design is simple random sampling (SRS). In this sampling design, each sampling unit is selected in the sample with equal probability. This sampling design can work if sampling units are homogeneous. First-order inclusion probabilities of all elements are equal. This random sample is known as a simple random sample. The random sample with replacement is more efficient than without replacement. Sampling with replacement implies that a selected element occurs again in the population before the next item is selected. There is a chance of choosing an item in the sample more than one time. Sampling without replacement implies that a selected element does not include the population. Therefore, there is no chance of choosing an item more than one time. The simple random sampling without replacement gives the precise estimates (Hansen, Hurvitz, & Madow, 1953).

2.9.5.2. *Stratified random sampling*

In stratified random sampling, the population are divided into a few groups according to some characteristics which are known as strata. A random sample is selected from each stratum with equal or proportional allocation. The mean or proportion can compute for each stratum which is unbiased estimates. Combining those mean or proportion can calculate an unbiased estimate of the population mean or percentage (Yates, 1949).

The stratified random sampling applies to many causes:

- Strata formed in such a way that they are homogeneous. The stratified sampling estimators will be more precise because of their homogeneity in stratum than simple random sampling estimates.
- There may be many situations where an estimate requires for population and sub-population. In this case, stratified random sampling is done instead of simple random sampling.
- The stratified random sample with equal allocation is more representative in strata.

This sampling design can only be applied when proper sampling frame is available. There must have individual sampling frame for each stratum. That is a limitation of stratified sampling. In this web survey, stratified random sampling design is used to create simulation of probability sample data where level of the faculty in the study is considered as strata. Open Education Faculty, Economics Faculty, and Business Administration Faculty are used as a stratum.

2.9.5.3. *Cluster sampling*

Cluster sampling can be used when sampling frame is incomplete for the sampling units in the target population. In cluster sampling, clusters make in such a way that within group, sampling units are heterogeneous, but between the groups are homogeneous. Simple random sampling selects a group, and all sampling units in the selected cluster are examined. For example, a cluster sample is a graduate individual where all individuals at a chosen graduate are requested to join in the study. This sampling does not provide precise estimates because more elements within a cluster are similar to each other. There is another merit of this study – no dominance over the sample size. The selected cluster's items are only taken into consideration in the sample (Deming, 1950).

2.9.5.4. *Two-stage sampling*

In two-stage sampling, a sample is chosen in two-stage. A sample of clusters is selected at first-stage, and then the desired sample of elements is observed in each selected cluster. This sampling design's applications are more useful than single-stage. This design will compute unbiased estimates, but it may be used for the scarcity of proper sampling design (Hansen, Hurvitz, & Madow, 1953). It may also reduce the costs. This design is applied when only interviewers collect data.

2.9.5.5. *Multi-stage sampling*

Multi-stage sampling design refers to sampling plans where the sampling conducts more than two stages and at each step smaller sampling unit are used. Multi-stage sampling can be a composite form of the cluster sampling design. Cluster sampling design is a type of sampling which comprises grouping the population into clusters or sub-population. Then, one or more clusters are chosen at random, and everyone within the selected group is sampled (Hansen, Hurvitz, & Madow, 1953). The advantages of this sampling are ability to minimize costs and can work quickly. It is a convenience sample survey. Usually, for the same size sample, cluster sampling more accurate than others.

2.9.5.6. *Systematic sampling*

Systematic sampling is a statistical system including the choice of elements from an ordered sampling frame of the population. The first standard type of systematic sampling is an equal-probability sampling technique. During this approach, sequence through the list is considered circularly—return to the starting point. The sampling begins choosing an element from the list randomly. So, each k^{th} element within the frame is selected automatically, where k^{th}, this sampling interval computes $k=N/n$, where n is that sample size and the population size is N. In this survey, each sampling unit has an equal certain probability of being selected in the sample. Simple random sampling selects the first sampling unit, and the rest are selected automatically (Rao, 2000).

2.9.5.7. *Convenience sampling*

Convenience sampling a process in which a sample is selected from readily available and convenient subjects. It is non-probability sampling. For example, in volunteer panel web surveys, the use of self-selection is a kind of convenience sampling (Tourangeau, Conrad, & Couper, 2013).

2.9.5.8. *Snowball sampling*

Snowball sampling utilizes a small pool of preliminary informer to propose, over their social networks, alternative members who have the eligible criteria and can contribute to a survey. The term "snowball sampling" represents a terminology to a snowball enlarging in size because of it rolling downhill (Johnson, 2014). This sampling utilizes suggestions to search out individuals with the level of expertise that has directed as being convenient person or group who collect information from entirely different places through a mutual intermediator. This useful tool makes networks and enlarging the participant's numbers. The success of this tool relies on the first contacts and making connections.

2.9.5.9. *Quota sampling*

In quota sampling, a population initially is divided into mutually exclusive sub-populations, even as in stratified sampling. It is a non-probability sampling. Then judgment is employed to pick out the sampling units from every phase based on a specified proportion. For example, a quota is made of 200 females and 300 males between the age 45 and 60 for a radio listening survey. The results of the study may have biased estimates because every individual has no opportunity of selection. It is beneficial when the survey period is restricted, an inaccessible sampling, the study budget is limited or when the accuracy of the estimates is not vital. Sub-groups selected based on the personal judgment of the researchers or survey administrators. The investigator decides what percentage of every group is chosen (Powers, & Xie, 2000).

2.9.5.10. *Purposive sampling*

Purposive sampling is a non-probability sampling design. It also refers to as judgmental or subjective sampling. In non-probability sampling, elements are selected based on the judgment of the researchers (Cochran, 1953). Several web surveys are conducted by non-probability sampling methods like convenience sampling. If a sample is not consistently representative of the population, the resulting estimates of population quantities may be biased.

2.10. Errors in Surveys

In the survey, researchers have the power in many aspects. They can obtain precise estimates by choosing a proper sampling frame, defining the target population, using an appropriate estimation tool, and applying proper sampling design. Unfortunately, everything is not in control. Researchers may face the challenge of various phenomena. They must focus on the data quality and reliability of the results (Deming, 1950). Some disturbances are not possible to control. The efforts are taken to reduce their impact as much as possible. Nevertheless, all attempts do not eliminate or reduce problems; estimates may be biased. The errors which arise due to estimating the parameter of the population by using a sample is called errors in the survey. There is a difference between actual value and the estimated value of the parameter and it is the total error of the estimate.

Errors may arise in surveys during the data collection mode, but in some studies, occur more errors (Cochran, 1953). It may be different whether interviewers conduct interviews, or the respondents complete the questionnaires themselves. The sources of error will compute biased estimates. It may appear in an estimator distribution in two ways: (1) it can tend to a systematic deviation (bias) from the actual population value, or (2) it can increase the variation around the actual value of the population parameter.

Suppose $\bar{y}$ be an estimator of the population mean $\bar{Y}$. For an estimator to call a right or precise estimator it must be unbiased (Hansen, Hurvitz, and Madow, 1953). It implies that sample estimate must be equal to the population mean. That can be written as

$$E\,(\bar{y})=\bar{Y} \tag{2.10}$$

Surveys errors lead to a biased estimator. Suppose we want to estimate the average time spend per day on the Internet. If a web sample is selected for it, only Internet accessing people will be in the sample. Otherwise, people who do not have Internet access will cause the estimate to be too high. The estimator will overestimate.

This bias of the estimator $\bar{y}$ is denoted as

$$B\,(\bar{y})= E(\bar{y})\text{-}\,\bar{Y} \tag{2.11}$$

The variance of the estimator

$$V\,(\bar{y})= E\,[\bar{y} - \,E(\bar{y})]^2 \tag{2.12}$$

should be small. An estimator is called precise if its variance is small. An estimator may be more precise when the sample size increases or auxiliary information is used.

A precise estimator may be biased. Therefore, a small variance of the estimate is not an indicator of the excellent estimator. A precise estimate indicates how much close estimate is to the true value. Mean squared error *(MSE)* is a better indicator of the precise estimator (Cochran, 1953).

$$MSE(\bar{y}) = E(\bar{y} - \bar{Y})^2 \tag{2.13}$$

It is the expected value of the squared difference of the estimator from the parameter value of the population. Equation (2.13) can be written the following expression.

$$MSE(\bar{y}) = V(\bar{y}) + B^2(\bar{y}) \tag{2.14}$$

where, $V(\bar{y})$ is the variance of the estimator, and $B^2(\bar{y})$ is the bias component squared. If the estimator is unbiased, mean squared error is the variance of the estimator. Mean squared error will be small if and only if both variance of the estimator and bias are small.

2.10.1. Classification of survey errors

The total errors can be classified into different errors. Firstly, it is classified into sampling error and non-sampling error. Secondly, these two types are classified into various kinds which has been shown in Figure 2.1.

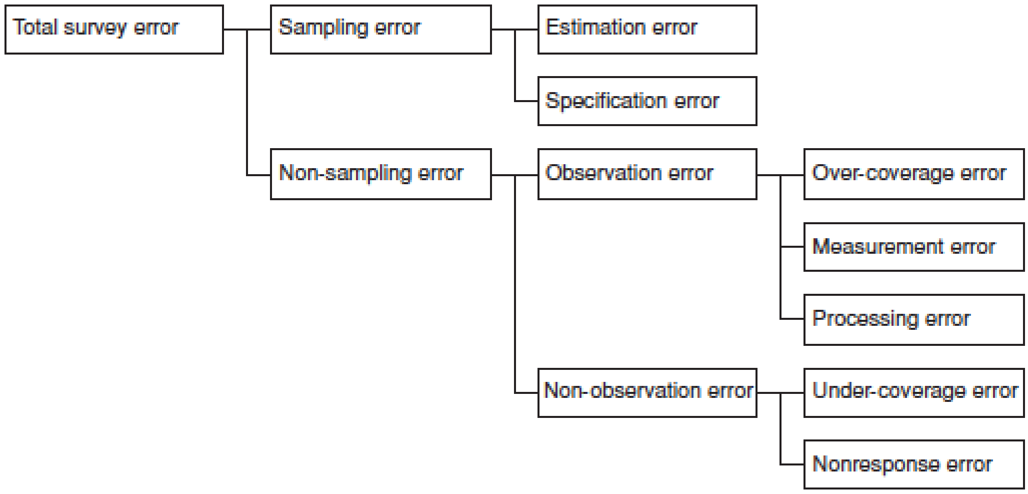

Figure 2.2. *Classification of surveys error (Bethlehem, 2012)*

2.10.1.1. *Sampling errors*

Sampling error occurs when the statistical characteristics of a population is estimated from a subset, or sample of that target population. It happens because the sample is used instead of complete enumeration of the population. This error disappears if the whole population is considered for estimation (Rao, 2000). Since sampling is usually done to work out the characteristics of an entire population, the distinction between the sample and population parameter values is considered as a sampling error. The estimation error and specification error are of sampling error types.

2.10.1.1.1. *Estimation error*

The estimation error denotes the effect caused by using a probability sample. Every new selection of a sample will result in a different set of elements and, thus, in a different value of the estimator. The estimation error can be controlled by the sampling design. For example, the estimation error can be reduced by increasing the sample size, or by taking selection probabilities proportional to the values of some well-chosen auxiliary variables.

Sampling errors do not depend on the mode of data collection (Tourangeau, Conrad, & Couper, 2013).

2.10.1.1.2. *Specification problem*

Wrong selection of probabilities in an estimator computation is a cause of specification error. This problem makes a biased estimate. If selection probabilities are known, resulting estimate will be an unbiased one. That unbiased estimator is called Horvitz–Thompson estimator. That estimator will be biased for using wrong selection probabilities. Probable and true selection probabilities' difference may cause problems in the sampling frame. Specification error happens in the self-selection web surveys. The true selection probabilities are not known in the self-selection respondents' recruitment. Usually, the sample mean can be used as an estimator of the population by assuming equal selection probabilities. But self-selection probabilities depend on the population characteristics, and there is a substantial variation (Schonlau et al., 2002). So, a specification error arises in the web survey for differing true selection probabilities from anticipated probabilities.

2.10.1.2. *Non-sampling error*

Besides the sampling error, the error which makes the estimate biased is called non-sampling error. It causes problems even though the whole population is being observed. It occurs during the process of getting the answer from the respondents. Non-sampling errors can cause observation errors and non-observation errors.

2.10.1.2.1. *Observation errors*

The first cause of non-sampling errors is observation errors. It may happen during the obtained answer processing, recording and further answer processing. Three types of observation errors are distinguished here: over-coverage errors, measurement errors, and processing errors.

- **Over-coverage error:** An over-coverage error occurs from selected elements in the sample which do not belong to the target population. Such items should not be chosen in the survey. They should be ignored. If such errors are not included in the survey data, estimators may be biased (Bethlehem, Cobben, & Schouten, 2011).

- **Measurement error:** The respondents' answers differ from the actual answer and may cause measurement error. There are some cases where it may occur as the answer not being understood, ignorance of the true answer, not interested in answering (Cobben, & Bethlehem, 2005). Measurement errors are a vital source of errors in web surveys.
- **Processing error:** A processing error happens during the data recording and processing for analysis. This error arises from respondents or interviewers when they write down answers mistakenly. Web surveys are free from processing error. However, mistakes can also be made if the questionnaire is on the Internet as clicking on the wrong answer is easy.

2.10.1.2.2. *Non-observation errors*

The second cause of non-sampling errors is non-observation errors. These errors occur if true estimation tool is not applied. Under-coverage errors and non-response errors are the two types of non-observation errors.

- **Under-coverage:** Under-coverage happens when the target population does not belong to the sampling frame. These elements should never be selected in a study. It can be a problem in web surveys if some items in the target population have no Internet access (Little, & Rubin, 2002). If a web survey is conducted for a general population, it may happen.
- **Non-response error:** Nonresponse error may arise if selected respondents do not give any information or the provided information is useless. It occurs in almost all the surveys when collecting data (Callegaro, Manfreda, & Vehovar, 2015). Non-response may differ from one group to another. Therefore, some items are overrepresented, and other groups are underrepresented.

3. DATA AND METHODOLOGY

This section consists of a brief description of the volunteer panel web survey, population, simulated random sample data as well as methodology of data analyses. The volunteer panel web survey data, the population data, random sample data, and the methodology of the data analysis describe in the following sections: 3.1, 3.2, 3.3, and 3.4 respectively.

3.1. Volunteer Panel Web Survey

The study conducts a volunteer panel web survey by self-selection—called a non-probability-based web survey. The survey title of this study *"Using Social Networking Sites in the Education of Students of Open Education System, Anadolu University"* has been conducted for an academic purpose to assist a study on the efficient use of the social networking sites in higher education at Anadolu University to enrich students' knowledge and learning. Respondents are members of a volunteer panel web of the Open Education System's students at Anadolu University (Buchanan et al., 2007). The panel web members (students) studies in one of the three faculties (Open Education, Business Administration, and Economics) at the Anadolu University and participated in the survey by self-selection. A web survey may occur under-coverage bias, self-selection bias, and non-response bias. The weighting adjustment techniques for reducing these biases have been illustrated in section 3.4 which will be explored by comparing the population estimates to those from the volunteer panel web survey.

3.1.1. Objective of the survey

The aim of the survey is to realize the level and perception of the using social networking sites in the education of students of Open Education System, Anadolu University. The survey's results are informed to the competent authority of Anadolu University in order that they may develop an up-to-date e-systems, especially, social networking sites.

3.1.2. Social networking sites (SNSs)

Social networking sites (SNSs) are online platforms those permit users to make a public profile and connect users on the websites. They usually have a new user lists of individuals. New users send a request to the existing users and then permit the individuals on the list to accept or reject the request. When connections are constituted, the new users can seek the webs of contacts to make more networks. Social networking sites are also known as social networking websites or social websites. Social networking sites can be used as community-based websites, online discussions forums, chat rooms, and other social spheres online (Hill et al, 2014). Blogs, Twitter, Facebook, LinkedIn etc. are examples of social networking sites.

3.1.3. Open Education System in the Anadolu University

The Open Education System at Anadolu University offers equal opportunity in higher education for all students who do not have access to campus-based higher education, including prison inmates as well as physically disabled individuals. The Open Education System of Anadolu University are committed to equal opportunity, goals to expose an extensive array of programs based on this value, and to offer sound learning atmospheres that the promoting programs are effective. Open Education System's students have a lot of facilities as textbooks accessing, joining TV programs, providing e-learning materials, conducting face-to-face classes, and all kinds of student care facilities, which are structured to meet student needs in the Open Education System. In academic session 1982-1983, Anadolu University Open Education Faculty was established. This is the first faculty which offered open and distance education in Turkey. This education system had 3003995 students in Spring, 2016-17. Among 3003995 enrolled students, 1043283 students were active students and 1960712 students were inactive. Over thirty years of experience, Anadolu university has a unique role in overcoming higher education problems in Turkey. Anadolu University Open Education System drives outside the country and provides higher education to Turkish citizens around the world, including those in the Turkish Republic of Northern Cyprus, Western Europe, Azerbaijan, Macedonia, Kosovo, Albania, and Bosnia-Herzegovina. There are three faculties in the Open Education System—Open Education Faculty, Faculty of Economics, and Faculty of Business Administration. In 1982, the Faculty of Open Education of Anadolu University was officially approved by the Higher Education Council as the institution responsible for offering continuous open education. Faculty of Economics offers courses through the Open Education System to meet the teaching requirements of the day. The Faculty of Economics has five departments these are:

Economics, Finance, Public Administration, Labor Economics and Industrial Relations, and International Relations. The Faculty of Business Administration pays to sound access to higher education and offers extensive opportunities to students, including virtual and manual class facilities. This faculty has the practical experience of providing competent and modern administration schooling for the years. The Faculty of Business Administration began its journey in 1993 after the reformation of Open Education System, which has been running distance education since the academic year 1982-1983.Three level of the program in the study in Open Education System are: Two-year associate degree program; Four-year Bachelor's degree program, and certificate program (htps://www.anadolu.edu./open-education/openeducationsystem).

3.1.4. Target population

The target variable *"using social networking sites in the education"* is considered as a response variable. The selected auxiliary variables in this study are regarded as predictors. The questionnaire consists of 26 questions (Appendix-1) where 1-8 are demographic questions, and 9-26 are *"using social network sites in the education"* related questions. The questionnaire is accessed using the link to web page. In the survey, Anadolu University Open Education System's web page (htps://www.anadolu.edu./open-education/openeducationsystem) has been used by the assistance of SurveyMonkey which is an online survey development cloud-based software as a service company (https://www.surveymonkey.net/ with link (https://tr.surveymonkey.com/r/9KSH2QL) to collect the desired data. The questionnaire link was set on 30 January 2017 on the website, and it was closed on 30 April 2017. Anadolu University's Open and Distance Education System had N= 3003995 students in Spring 2016-2017. All 3003995 students of the Open Education System are the target population. Among 3003995 enrolled students 1043283 (34.73%) students were active students and 1960712 (56.27%) students were inactive. Total of 2920 respondents participated in the survey. The reliability of the volunteer panel web survey data is 62.3%. This study has only been used the seven demographic auxiliary variables to estimate the target variable. The selected auxiliary variables in this study are*: Gender, Age, Region, Working status of respondents, Marital status, Level of the program in the study, and Faculty in the study***.**

3.1.5. Volunteer panel web survey data

The percentage distribution of the volunteer web survey data has been represented in Table 3.1. The target variable is *"using social networking sites in the education"*. The volunteer panel web sample size is 2920. The first auxiliary variable, *Gender*, which is divided into two categories: male and female. The percentage of male respondents (57.70%) is greater than female respondents (42.30%). The auxiliary variable Age which is grouped into seven categories. The maximum (32.50%) response occurs in the age group 20-25 years whereas lowest (3.30%) response rate belongs to the age group <20 years. The 8.20% respondents are from rural region whereas 44.20% and 47.60% are from urban and metropolitan area respectively. The *Working status* which is divided into three categories. The most significant (58.30%) respondents have a full-time job, and lowest (8.10%) respondents have a part-time job, but 47.60% respondents have no responsibility. The variable *Marital status* of the respondents has four categories. Never married/single respondents are 56.20%, married respondents are 39.90%, divorced respondents are 2.80%, and 1.10% are widowed. The *Level of the program in the study* is divided into two categories: two-year associate degree program and Four-year Bachelor's degree program. The proportion of the two-year associate degree program is 45.10% whereas four-year bachelor's degree is 54.90%. The last auxiliary variable *Faculty in the study* is divided into three categories: Open Education Faculty, Economics Faculty, and Business Administration Faculty. The most 84.30% respondents are from Open Education Faculty, 8.20% respondents are from Economics Faculty, and 7.50% respondents are from Business Administration Faculty. The percentage of using social networking sites in the education is 57% and not using social networking sites in the education is 43%.

Table 3.1. *Percentage distribution of responses of selected variables for the volunteer panel web survey*

Variable	Category	Number of responding	Percentage (%)
Gender	Male	1684	57.70
	Female	1236	42.30
Age (year)	<20	95	3.30
	20-25	949	32.50
	25-30	818	28.00
	30-35	382	13.10

Table 3.1. (Continued) *Percentage distribution of responses of selected variables for the volunteer panel web survey*

Variable	Category	Number of responding	Percentage (%)
	35-40	224	7.70
	40-4	140	4.80
	45^{+}	312	10.70
Region	Rural	239	8.20
	Urban	1290	44.20
	Metropolitan	1391	47.60
Working status	Not working	982	33.60
	Part-time working	236	8.10
	Full-time working	1702	58.30
Marital status	Single/Never married	1641	56.20
	Married	1165	39.90
	Divorced	82	2.80
	Widowed	32	1.10
Level of program in the study	Two-year associate degree	1317	45.10
	Four-year Bachelor's degree	1603	54.90
Faculty in the study	Open Education	2463	84.30
	Economics	239	8.20
	Business Administration	218	7.50
Using SNSs in the education	Yes	1665	57
	No	1255	43
Total		**2920**	**100**

3.2. Population Data

In this study, the population is the total students of the Open Education System, Anadolu University in Spring 2016-2017. The students of Open Education System have been taken in the study because all the students have access to the Internet. Web surveys can be performed when all sampling units in the population have access to the Internet. Individuals without Internet access have not been selected in the web sample.

The Open and Distance Education System of Anadolu University had 3003995 students in Spring, 2016-17. Among 3003995 enrolled students 1043283 (34.73%)

students were active students and 1960712 (56.27%) students were inactive. Importantly, this study observes only the active students. There are 1043283 active students in that semester. Thus, the target population size is $N = 1043283$. The target variable is "*using social networking sites in the education*". The selected auxiliary variables information is available, but the target variable information is not available. Therefore, a simulation has been done for creating the population data of the target variable utilizing auxiliary information. A simulated population of size 1043283 has been created. The variables list is given below:

- Gender has two categories: female (probability 0.41) and male (probability 0.59).
- Age has seven categories: <20 years (with probability 0.031), 20-25 years (with probability 0.125); 25-30 years (with probability 0.145); 30-35 years (with probability 0.135); 35-40 years (with probability 0.12); 40-45 years (with probability 0.105); and 45^+ years (with probability 0.335).
- The region has three categories: rural (with probability 0.075); urban (with probability 0.435); and metropolitan (with probability 0.49).
- Working status of the respondents has three categories: not-working (with probability 0.325) part-time working (with probability 0.073) and full-time working (with probability 0.602).
- Marital status has four categories: never married/single (with probability 0.579); married (with probability 0.39); divorced (with probability 0.025); and widowed (with probability 0.06).
- Level of the program in the study has two categories: two-year associate degree (with probability 0.441); and four-year bachelor's degree program (with probability 0.559).
- Faculty of the study has three categories: Open Education Faculty (with probability 0.50); Economics Faculty (with probability 0.26); and Business Administration Faculty (with probability 0.24).
- The target variable "*using social networking sites in the education*" has two categories: no (with probability 0.412); and yes (with probability 0.588).

Table 3.2. *Percentage distribution of the population data*

Variable	Category	Frequency	Percentage (%)
Gender	Male	615421	59.00
	Female	427862	41.00
Age (year)	<20	32822	3.10
	20-25	130550	12.50
	25-30	155241	14.90
	30-35	140547	13.50
	35-40	124928	12.00
	40-45	109852	10.50
	45^{+}	349343	33.50
Region	Rural	78586	7.50
	Urban	453848	43.50
	Metropolitan	510849	49.00
Working status	Not-working	338556	32.50
	Part-time working	76552	7.30
	Full-time working	628175	60.20
Marital status	Single/Never married	604478	57.90
	Married	406557	39.00
	Divorced	25992	2.50
	Widowed	6256	0.60
Level of program in the study	Two-year associate degree	460328	44.10
	Four-year Bachelor's degree	582955	55.90
Faculty in the study	Open Education	934369	89.60
	Economics	55627	5.30
	Business Administration	53287	5.10
Using SNSs in the education	Yes	613515	58.80
	No	429768	41.20
Total		**1043283**	**100**

Table 3.2 shows the percentage distribution of the population data. The target population size is 1043283. The auxiliary variable *Gender* has two categories: male and female. The proportion of male respondents (59.00%) is greater than female respondents (41.00%). The *Age* variable is divided into seven categories. The most significant (33.50%) response is observed in the age group 45^{+} years whereas smallest (3.10%)

respondents belongs to the age group <20 years and other age group 20-25 years, 25-30 years, 30-35 years and 40-45 years proportion do not differ more with one another age group. The 7.50% respondents are from rural region where 43.50% and 49.00% are from urban and metropolitan area respectively. The *Working status* variable has three categories. The most significant (60.20%) respondents have a full-time job, and lowest (7.30%) respondents have a part-time job, but 32.50% respondents have no responsibility. The *Marital status* has four categories. The maximum 57.90% respondents are never married/single where married respondents are 39.00%, divorced respondents are 2.50%, and 0.60% are widowed. The *Level of the program in the study* has two categories: two-year associate degree program and Four-year Bachelor's degree program. The percentage of the two-year associate degree program is 44.10% whereas Four-year Bachelor's degree is 55.90%. There are three categories of the variable *Faculty in the study* as Open Education Faculty, Economics Faculty, and Business Administration Faculty. The 89.60% respondents are from the Open Education Faculty, 5.30% respondents are from the Economics Faculty, and 5.10% respondents are from the Business Administration Faculty. However, the 58.80% respondents use social networking sites in the education.

3.3. Random Sample Data

To explore how effective probability-based web surveys than volunteer panel web surveys (non-probability-based), a stratified random sample has been created by a simulation. The target variable of the simulated random sample is *"using social networking sites in the education"*. As the target population size is N = 1043283, so that a stratified random sample is n = 2396 (margin of error 2% and confidence interval 95%). There are three faculties in the Open Education System of the Anadolu University which are: Open Education Faculty, Economics Faculty, and Business Administration Faculty. Each faculty has been considered as a stratum. Therefore, there are three strata. Proportion allocation has been used for taking the random sample from the strata. A simulated random sample of eight variables is given below:

Table 3.3. *Percentage distribution of selected variables for the random sample data*

Variable	Category	Number of responding	Percentage (%)
Gender	Male	1423	59.40
	Female	973	40.60
Age (year)	<20	69	2.90
	20-25	276	11.50
	25-30	362	15.10
	30-35	326	13.60
	35-40	264	11.00
	40-45	269	11.20
	45^+	830	34.60
Region	Rural	163	6.80
	Urban	1022	42.70
	Metropolitan	1211	50.50
Working status	Not-working	776	32.00
	Part-time working	181	7.60
	Full-time working	1449	60.50
Marital status	Single/Never married	1390	58.00
	Married	925	38.60
	Divorced	60	2.50
	Widowed	21	0.90
Level of program in the study	Two-year associate degree	1069	44.60
	Four-year Bachelor’s degree	1327	55.40
Faculty in the study	Open Education	1211	50.50
	Economics	630	26.30
	Business Administration	555	23.20
Using SNSs in the education	Yes	1411	58.90
	No	985	41.10
Total		**2396**	**100**

Table 3.3 illustrates the percentage distribution of the simulated random sample data. The study has seven auxiliary variables which have been selected in the volunteer panel web survey. The target variable is “*using social networking sites in the education*”. The simulated random sample size is 2396. There are two categories in the *Gender*

variable as male and female. The proportion of female respondents (40.60%) is smaller than male respondents (59.40%). The variable *Age* has seven categories. The lowest (2.90%) response is observed in the age group <20 years whereas largest (34.60%) respondents belongs to the age group 45^+ years and percentages of the response rates of the age group 20-25 years, 25-30 years, 30-35 years, 35-40 years, and 40-45 years are 11.50, 15.10, 13.60, 11 and 11.20 respectively. There are three categories in the *Region*. The 6.80% respondents are from the rural area where 42.70% are from urban, and 50.50% are from the metropolitan area. The *Working status* variable has three categories. The 60.50% respondents have a full-time job and 7.60% respondents have a part-time job, but 32.00% respondents have no responsibility. The *Marital status* has four categories. Maximum 58.00% respondents are never married/single where married respondents are 38.60%, divorced respondents are 2.50%, and 0.90% are widowed. The *Level of the program in the study* has two categories as Two-year associate degree program and Four-year Bachelor's degree program. The response of the Two-year associate degree program (44.60%) is smaller than Four-year Bachelor's degree (55.40%). There are three categories of the *Faculty in the study*: Open Education Faculty, Economics Faculty, and Business Administration Faculty. The 50.50% respondents have come from the Open Education Faculty, 26.30% respondents have come from the Economics Faculty, and 23.20% respondents have come from the Business Administration Faculty. The proportion of the using social networking sites in the education is 58.90% whereas not using of social networking sites in the education is 41.10%.

3.4. Methodology

In web surveys, bias may arise mainly due to under coverage, self-selection and non-response errors. The data can be adjusted to correct these errors. Mainly, weighting adjustments are a potential resolution to improve the quality of web surveys (Bethlehem and Stoop 2007, & Dever et al. 2008). Weighting adjustments are techniques that used to reduce the bias of estimates by using auxiliary variables (Bethlehem, 2010). The utilized weighting adjustment techniques for reducing the bias in web surveys are post-stratification weighting, propensity score adjustment, rim weighting and generalized regression modeling (Lee, 2004; Bethlehem, 2010; & Steinmetz et al., 2009).

Table 3.4. *Type of weighting adjustment techniques (Kalton & Flores-Cervantes, 2003)*

Weighting Adjustments Techniques
1. Post-stratification or weighting class adjustments
2. Generalized regression modeling
3. Raking ratio or rim weighting
4. Propensity score adjustment (PSA)

3.4.1. Post-stratification weighting technique

Post-stratification weighting is an adjustment estimation technique that reduce the non-coverage and non-response biases as well as variance of the estimates (Cervantes et al., 2009). It is utilized to adjust weight for demographic variable's differences between a sample and the population. Looseveldt and Sonck (2008) argued that the technique does not resolve the problem of selection bias since some response variables may be associated with variables apart from demographics characteristics. For example, attitudinal and behavioral differences may be observed even when applying the post-stratification weighting adjustment using demographic variables.

Post-stratification needs one or more auxiliary variables. An auxiliary variable is a variable that is measured in the survey, and that the distribution of the target population is available. In this study, the target variable is "*using social networking sites in the education"*. Percentage distribution of auxiliary variables of the volunteer panel web survey are compared with its population to assess whether the conducted survey is representative to the population. If these distributions do not differ, it may be concluded that the conducted survey response is nonresponsive. Adjustment weights are calculated for this correction. Weights assess any or all register of observed elements. Population estimates can be computed utilizing the weighted values rather than the unweighted values.

3.4.1.1. *Under coverage case*

Post-stratification is performed on one or more categorical auxiliary variables. In this study, seven auxiliary variables have been implemented. Suppose that auxiliary variable X_1 has L categories. So, it is divided the target population into L subgroups. Similarly, it can be done for all auxiliary variables. The subgroups are symbolized by the subsets $U_1, U_2, \ldots, U_L$ of the target population U. The target population element's numbers in stratum U_h is expressed by N_h, for $h=1, 2, \ldots, L$. The population size N is equal to $N=N_1+N_2+\ldots+N_L$. This population data has been created by simulation where the size of the population is N=1043283.

The study has a volunteer panel web sample of size n = 2920. In stratum h, the number of sample elements is denoted by n_h, then $n = n_1 + n_2 + \cdots + n_L$. The values of the n_h are the outcome of a random selection procedure, so, they are random variables. It is noted that since the sample is collected from the Internet access population, only elements in the sub-strata $U_I \cup U_h$ are detected (*for $h=1, 2, \ldots, L$).*

For each stratum, post-stratification is allotted adjustment weights which are identical. The correction weight c_i for h stratum is equal to

$$c_i = \frac{N_h/N}{n_h/n} \tag{3.1}$$

where N_h is the size of stratum h; n_h is the sample size of stratum h; N is the total target population and n is the sample size. If the values of the inclusion weights d_i=N/n, then the post-stratification adjustment weights w_i are found by multiplying the correction weights c_i and the inclusion weights d_i as $w_i = c_i \times \; d_i$. The weighted estimate would be $c_i \times d_i \times n_h$.

Post-stratification weight derives down to substituting the simple sample mean

$$\overline{y_I} = \frac{1}{n} \sum_{k=1}^{N} a_k \, I_k Y_k \tag{3.2}$$

by the weighted sample mean

$$\overline{y_{I,PS}} = \frac{1}{n} \sum_{k=1}^{N} a_k \, w_k I_k Y_k \tag{3.3}$$

Substituting the weights and the equation (3.3) tends to the post-stratification mean estimator

$$\overline{y_{I,PS}} = \frac{1}{N} \sum_{k=1}^{L} N_h \, \overline{y_I}^{(h)} = \sum_{k=1}^{L} W_h \, \overline{y_I}^{(h)} \tag{3.4}$$

where $\overline{y_I}^{(h)}$ is the h^{th} stratum sample mean and $W_h = \frac{N_h}{N}$ is the h^{th} stratum relative size. Post-stratification mean estimator expected value is equal to

$$E\,(\overline{y_{I,PS}}) = \frac{1}{N} \sum_{k=1}^{L} N_h \, E(\overline{y_I}^{(h)}) = \sum_{k=1}^{L} W_h \, \overline{Y_I}^{(h)} = \widetilde{Y_I} \tag{3.5}$$

where, $\overline{Y_I}^{(h)}$ is the target variable mean of h^{th} stratum Internet population.

Usually, this mean will not be equal to the mean $\overline{Y_I}^{(h)}$. The biased estimator is written as:

$$B\,(\overline{y_{I,PS}}\,)= \; E\,(\overline{y_{I,PS}}) - \overline{Y} = \widetilde{Y_I} - \overline{Y} = \sum_{k=1}^{L} W_h\,(\overline{Y_I} - \overline{Y}^{(h)})$$

$$= W_h \frac{N_{NI,h}}{N_h}\left(\overline{Y_I}^{(h)} - \overline{Y_{NI}}^{(h)}\right) \tag{3.6}$$

where $N_{NI,h}$ is the h^{th} stratum number of elements of the non-Internet population.

The variance of post-stratification mean estimator which is defined by (3.4) has no simple expression. That can be expressed by large sample approximation as

$$V(\overline{y_{ps}}) = (\frac{1}{n} - \frac{1}{N}) \sum_{h=1}^{L} W_h {S_h}^2 + \frac{1}{n^2} \sum_{h=1}^{L} (1 - W_h) {S_h}^2 \tag{3.7}$$

where $W_h = N_h/N$ is the h^{th} stratum relative size and ${S_h}^2$ is the h^{th} stratum population variance of the target variable.

The mean estimator by post-stratification is precise if within strata there have a homogeneity for the target variable. This means that the target variable variation is occurred by changes in means between strata, not by within strata variation. The standard error of the post-stratification mean estimator is the square root of the variance of the mean estimator (Bethlehem and Biffignandi, 2012).

Post-stratification proportion estimator is defined as

$$\widehat{p_{ps}} \; = \frac{1}{N} \sum_{h=1}^{L} N_h \widehat{p_h} \tag{3.8}$$

where N_h is the h^{th} stratum population size and $\widehat{p_h}$ is the sample proportion of the h^{th} stratum.

The variance of the post-stratification proportion estimator (Rao, 2000) is defined by

$$V(\widehat{p_{ps}}) = \; \frac{1}{N} \sum_{h=1}^{L} {N_h}^2 \; \left(\frac{N_h - n_h}{N_h}\right) . \frac{\widehat{p_h}(1 - \widehat{p_h})}{(n_h - 1)} \tag{3.9}$$

If there is no variation between elements in the sample access to the Internet and no access to the Internet, then bias will be less. This may be often happened if target variable and auxiliary variable are strongly correlated. The variation of target variable values can be occurred only between strata. Especially, strata are made in such a way that sampling units are homogeneous to target variable. Missing at random (MAR) is considered as non-response which are correlated with target variable(s).

The post-stratification application can be practical if actual auxiliary variables can be explored. Such type of variables should satisfy the following conditions (Bethlehem and Biffignandi, 2012):

- Auxiliary variables must be determined inside the survey.
- Population distribution *(N_1, N_2, …, N_L)* must be identified.
- Auxiliary variable must have a strong correlation with all target variables.

3.4.1.2. *Self-selection case*

Post-stratification is equivalent to replacing the sample mean

$$\overline{y_S} = \frac{1}{n_S}\sum_{k=1}^{N} R_k\, Y_k \tag{3.10}$$

where, R_k is the k^{th} response element and $n_S = \sum_{k=1}^{N} R_k$ is the registered sample size. With the weighted sample mean

$$\overline{y_{S,PS}} = \frac{1}{n_S}\sum_{k=1}^{N} R_k\, w_k Y_k \tag{3.11}$$

replacing the weights and turns equation (3.11) to the post-stratification estimator

$$\overline{y_{S,PS}} = \frac{1}{N}\sum_{k=1}^{L} N_h\, \overline{y_S}^{(h)} = \sum_{k=1}^{L} W_h\, \overline{y_S}^{(h)} \tag{3.12}$$

where $\overline{y_S}^{(h)}$ is the h^{th} stratum sample mean and $W_h = \frac{N_h}{N}$ is the h^{th} stratum relative size. The mathematical expectation of this post-stratification estimator which is defined in equation (3.12) is:

$$E\,(\overline{y_{S,PS}}) = \frac{1}{N}\sum_{k=1}^{L} N_h\, E\,(\overline{y_S}^{(h)}) = \sum_{k=1}^{L} W_h\, \overline{Y_I}^{(h)} = \widetilde{Y^*} \tag{3.13}$$

where $\widetilde{Y^*} = \frac{1}{N}\sum_{k=1}^{N_h} \frac{\rho_{k,h}}{\overline{\rho_h}} Y_{k,h}$ is the weighted mean of the target variable in stratum h. The subscript (k, h) denotes the k^{th} element in stratum h, and $\overline{\rho_h}$ is the average response probability in stratum h.

Normally, this mean is not exactly equal to the h^{th} stratum target variable population mean $\overline{Y_h}$. The bias of this estimator is:

$$B\,(\overline{y_{S,PS}}\,) = E\,(\overline{y_{S,PS}}) - \overline{Y}$$

$$= \widetilde{Y^*} - \bar{Y}$$

$$= \sum_{k=1}^{L} W_h \, (\bar{Y_S} - \bar{Y}^{(h)})$$

$$= W_h \frac{R_{\rho Y}{}^{(h)} S_Y{}^h}{\overline{\rho^{(h)}}} \qquad (3.14)$$

The bias (3.14) will be small if

- Response propensity score of each element of the sample in strata is identical.
- The target variable values are similar within strata.
- The target variable and response within strata is not correlated (Bethlehem and Biffignandi, 2012)

3.4.2. Propensity score adjustment (PSA)

Propensity score adjustment (PSA) is recommended as an alternate for statistically prevailing intrinsic complications in web survey data (Loosveldt and Sonck 2008, & Schonlau et al. 2009). The purpose of the PSA is to correct differences caused by the differing tendencies of individuals to join in web surveys (Duffy et al. 2005). It is adjusted for selection bias which is observed in the demographic variable as well as "webographic" (lifestyle/attitudinal) variables measuring where web sample is differed from the general population (Schonlau et al. 2007).

Propensity scores are obtained by modeling a variable that specifies whether individual/member takes part in the survey. A logit regression model is utilized where the dependent variable is the dichotomous indicator variable, and the explanatory variables are the demographic variables.

The logit regression model is fitted by using observed sample data and compute the probability of participating in the survey which has termed as propensity score condition to the auxiliary variables values.

In the target population, each k elements are assumed to have a specific, unknown probability of joining 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 survey participants, if an individual is observed X characteristics, then the propensity score is the conditional probability which is defined below:

$$\rho(X)=P\ (R = \frac{1}{X}) \qquad (3.15)$$

Strata are made of the values of the observed characteristics *X*. It is assumed that all members of the strata have the equal probability. This assumption is called MAR assumption. This assumption is also called conditional independence assumption (Lechner, 1999), selection on observables (Barnow et al., 1980), not-confoundedness assumption or ignorable treatment assumption (Rosenbaum and Rubin, 1983), and homogeneity (Imbeans, 2004).

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

$$log(\frac{\rho(X_{k)}}{1-\rho(X_{k)}}) = \alpha + \beta' X_k \qquad (3.16)$$

For fitting the model, maximum likelihood estimation is used. The propensity scores are calculated by stratifying the population. Strata are created in such a way that within strata, they are homogeneous and between layers are heterogeneous. Therefore, each level has elements with an approximate equal propensity score. There will have a bias if all items within a stratum have not a similar response propensity. A significant amount of bias will be removed, if propensity scores have five levels (Lee, 2011).

The propensity score weighting should be adequate to reduce the bias theoretically. But, in practice, propensity score is considered as a variable which typically is combined with another (demographic) variables throughout further continued weighting procedure (Schonlau et al. ,2004).

Usually, the logit model has utilized for estimating probabilities of participating in the survey, which are called response propensities. Revising model (3.16) leads to the expression

$$\rho(X_{k)} = \frac{exp(\beta' X_k)}{1+exp(\beta' X_k)} \qquad (3.17)$$

for the probabilities. The response propensities estimation not only relies on the availability of data but also have both non-respondents and respondents' values for auxiliary variable *X*. This indication is called the matching assumption. It defines that

$$0 < \rho(X_{k)} < 1 \qquad (3.18)$$

This assumption indicates that against each value of the auxiliary variable X, there are individuals who join in the web survey and individuals who do not participate in the study.

It is mentionable that response probability of the respondents equal to 0 or 1. It has not compared since there are no counterparts of the individuals. The notation $\rho(X_k)=1$, means that k^{th} individual participates in the study and $\rho(X_k)=0$, indicates that k^{th} individual does not participate in the survey. But, unfortunately, they never be observed. Thus, this is the reason of bias. This bias is called selection bias. When logit regression modeling estimates are used for response propensities, viable selection bias may be removed by them (Schonlau et al., 2004). The response propensity weighting and response propensity stratification are the approaches of PSA.

3.4.2.1. *Response propensity weighting case*

Response propensity weighting is a technique that follows survey sampling principles that compute and constructs unbiased estimators if observed elements have known selection probabilities. In selection problems case (under-coverage, nonresponse, and self-selection), the actual selection probability of an individual is the selection probability's result. The computed propensities of response are substituted by the unknown probabilities of the responses. If every sample element is observed properly, the Horvitz–Thompson estimator is symbolized by

$$\overline{y_{HT}}=\frac{1}{N}\sum_{k=1}^{N} a_k \frac{Y_k}{\pi_k} \tag{3.19}$$

This is an unbiased estimator of the population mean. The a_k indicator variable is signified whether the k^{th} element is selected in the web sample ($a_k = 1$) or not ($a_k = 0$), and π_k is the k^{th} element's inclusion probability of first-order.

In the case of non-response, ρ_k is the k^{th} sample response probability. It is a certain value, but unknown. The Horvitz–Thompson (1952) estimator can be modified by substituting these response probabilities for removing bias which is written as

$$\overline{y_{HT,R}}=\frac{1}{N}\sum_{k=1}^{N} a_k R_k \frac{Y_k}{\pi_k \rho_k} \tag{3.20}$$

where R_k is specified whether k^{th} element responses. This estimator is an unbiased estimator. This estimator can be computed when the values of the ρ_k are known. If computed response propensity $\rho(X_{k)}$ is substituted in the ρ_k of equation (3.20) then it turns to

$$\overline{y_{HT,R}}=\frac{1}{N}\sum_{k=1}^{N} a_k\, R_k \frac{Y_k}{\pi_k \hat{\rho}(X_k)} \tag{3.21}$$

This modified estimator will be approximately an unbiased estimator if the appropriate model is utilized (Horvitz and Thompson, 1952).

3.4.2.2. *Stratification of response propensity case*

Response propensity holds an advantage of the fact that estimates will be biased if all response probabilities are not equal. In this situation, selection problems are happened only for a small number of observations, but it is not affected the sample composition. The concept is that the sample is divided into subgroups which are called strata, where each stratum consists of approximately similar response probabilities. Consequently, within strata, unbiased estimates can be obtained. Thus, population estimate can be found by combining the estimates of the stratum. The final estimates of the stratification of response propensities depend on the appropriate use of the model for computing response propensities.

In this case, the approximate values estimate the computation. Strata are constructed using these probabilities. Thus, propensity score of *X* auxiliary variable is *ρ(X)* which is smoothened.

Suppose, the observed sample is classified into L strata based on the response propensities. The strata numbers are denoted by *h* which is denoted by U_1, U_2,...., U_L. The h^{th} stratum sample size is indicated by n_h. The sample strata sizes vary among each other. Therefore, these sample sizes are random variables. It assumes that strata sizes can constructed by a simple random sampling. The estimator of response propensity of population mean (Bethlehem and Biffignandi, 2012) for target variable *Y* is symbolized by

$$\overline{y_{RPS}} = \frac{1}{n}\sum_{k=1}^{N} n_h\, \overline{y_R}^{(h)} \tag{3.22}$$

where $\overline{y_R}^{(h)}$ is the h^{th} stratum mean of the respond elements, for *h=1, 2, …, L*.

3.4.3. Generalized regression modeling

The generalized regression estimator is computed when the relationship between target variables and auxiliary variables is a linear. The aim is to illustrate unbiased estimators of target variables by generalizing models. These estimators can be produced precise estimates as well as reduce the bias. In fact, this is shown that it is a weighting form of variables.

In generalized regression modeling, the results of weighting make the typical response according to the auxiliary information in the model. It is shown that the generalized regression modeling is a generalization of post-stratification weighting.

It assumes that data are collected by simple random sampling without replacement (Bethlehem, 1988) and it can also do for other sampling designs. Firstly, there is no bias (ideal case) is considered. Suppose, there are p continuous auxiliary variables.

For the k^{th} element of the values of auxiliary variables vector p is expressed as

$$X_k = (X_{k1,}X_{k2}, \dots, X_{kp})' \tag{3.23}$$

Suppose that *Y* be the target variable which has values of *N*-vector and let *X* be the auxiliary variable of consisting values of $N\times P$-matrix. The population means' vector of the p auxiliary variables is defined by

$$\bar{X} = \left(\overline{X_1}, \overline{X_2}, \dots, \ \overline{X_p}\right)' \tag{3.24}$$

It assumes that the vector of equation (3.24) indicates the available population information.

This vector represents the population information which assumed to be available. If the selected auxiliary variables are associated with the target variable, then the regression of Y on X fits the best, and their regression coefficients vector is $B = (B_{1,}B_2, \dots, B_p)'$, the residuals $E = (E_{1,}E_2, \dots, E_p)'$ is defined by

$$E = Y - XB \tag{3.25}$$

which will not differ more than the values of the target variable itself. All residuals will be zero, if there is a perfect correlation between target variables and auxiliary variables.

The ordinary least squares estimator of the target variable which is approximated by

$$B = (X'X)^{-1}X'Y = \left(\sum_{k=1}^{N} X_k\, X_k{}'\right)^{-1}\left(\sum_{k=1}^{N} X_k Y_k\right) \tag{3.26}$$

In the case of simple random sample without replacement, the estimator B vector can be calculated by

$$b = (\sum_{k=1}^{N} a_k X_k X_k{'})^{-1} (\sum_{k=1}^{N} a_k X_k Y_k) = (\sum_{i=1}^{n} x_i x_i{'})^{-1} (\sum_{i=1}^{n} x_i y_i) \qquad (3.27)$$

where $x_i = (x_{i1,} x_{i2}, \dots, x_{ip})'$, is symbolized i^{th} sample elements of p-auxiliary variables values' vector, for $i=1, 2, \dots, n$. The quantity a_k is the k^{th} selected element in the sample that is an asymptotically unbiased estimator of B. It implies that for large samples, the bias of the estimator is disappeared. Now, the generalized regression estimator can be defined as

$$\overline{y_{GR}} = \bar{y} + (\bar{X} - \bar{x})' b \qquad (3.28)$$

where, $\bar{x}$ is the sample means the vector of the selected auxiliary variables.

The generalized regression estimator is an asymptotically unbiased estimator of the population mean of the target variable. If there exists a p-vector c of fixed numbers such that $X_c = J$, where J is a p-vector consisting of 1's, the generalized regression estimator (Bethlehem and Keller, 1987) can also be written as

$$\overline{y_{GR}} = \bar{X}' b \qquad (3.29)$$

It can be shown that the variance of the generalized regression estimator is approximated by

$$V(\overline{y_{GR}}) = \frac{1-f}{n} {S_E}^2 \qquad (3.30)$$

where ${S_E}^2$ is the population variance of the residuals $E_{1,} E_2, \dots, E_N$.

If generalized regression estimator is used, then the form of the estimator and its variance is changed. It may occur for two cases which has shown below:

3.4.3.1. *Under-coverage case*

For the under-coverage, the generalized regression estimator is transformed to

$$\overline{y_{GR,I}} = \overline{y_I} + (\bar{X} - \overline{x_I})' b_I = \bar{X}' b_I \qquad (3.31)$$

The subscript I indicates Internet accessing population. The coefficients' vector b_I is defined by

$$b_I = (\sum_{k=1}^{N} a_k I_k X_k X_k{'})^{-1} (N \sum_{k=1}^{N} a_k I_k X_K Y_K) \qquad (3.32)$$

where, a_k is k^{th} indicator of the sample and I_k is the k^{th} indicator of the Internet. So, estimation of b_I is made based on Internet population data. Bethlehem (1988) showed that the approximation of biased estimator is equal to

$$B\left(\overline{y_{GR,I}}\right) = \bar{X}\, B_I - \bar{Y} = \bar{X}(B_I - B) \tag{3.33}$$

where B_I is defined by

$$B_I = \left(\sum_{k=1}^{N} I_k X_k X_k{}'\right)^{-1}\left(\sum_{k=1}^{N} I_k X_k Y_k\right) \tag{3.34}$$

If $B_I = B$, then the estimator is unbiased. Therefore, the regression estimator will be biased if under-coverage does affect the regression coefficients, otherwise, unbiased. If the association between response and auxiliary variables is strong, the wrong relationship risk finding is less. By rewriting

$$B_I = B + \left(\sum_{k=1}^{N} I_k X_k X_k{}'\right)^{-1}\left(\sum_{k=1}^{N} I_k X_k E_k\right) \tag{3.35}$$

the inference can be done that the small residuals will lead to small. This theory illustrates that generalized regression estimator reduces the potential bias in the sample (Bethlehem and Biffigandi, 2012).

3.4.3.2. *Self-selection case*

Self-selection, the estimator computed by generalized regression modeling turns to

$$\overline{y_{GR,S}} = \overline{y_S} + (\bar{X} - \overline{x_S})' b_S = \bar{X}' b_S \tag{3.36}$$

The subscript *S* indicates the self-selected sample values. The coefficients vector b_S is denoted by

$$b_S = \left(\sum_{k=1}^{N} R_k X_k X_k{}'\right)^{-1}\left(\sum_{k=1}^{N} R_k X_k Y_k\right) \tag{3.37}$$

where, R_k is the k^{th} element's response indicator. The approximation of the estimator of equation (37) is:

$$B\left(\overline{y_{GR,S}}\right) = \bar{X}\, B_S - \bar{Y} = \bar{X}(B_S - B) \tag{3.38}$$

where B_S is defined by

$$B_S = \left(\sum_{k=1}^{N} \rho_k X_k X_k{}'\right)^{-1}\left(\sum_{k=1}^{N} \rho_k X_k Y_k\right) \tag{3.39}$$

The bias of this estimator will be disappeared if B_S=*B*. Hence, the generalized regression estimator will be unbiased if there is no self-selection effect on the regression coefficients. If associations are strong, the wrong relationship finding risk is small. By writing

$$B_S = B + (\sum_{k=1}^{N} \rho_k X_k X_k{}')^{-1}(\sum_{k=1}^{N} \rho_k X_k E_k) \tag{3.40}$$

this expression indicates that the small residuals will lead small bias. This theory indicates that the generalized regression estimator is removed the potential bias of self-selection (Bethlehem and Biffigandi, 2012).

3.4.4. Raking ratio estimation

Raking ratio estimation is used when there is a log-liner relationship between target variables and auxiliary variables in the data. Generalized regression estimators are obtained by taking the sum of weight coefficients. If correction factors are computed as the product of several factors of weight, this weighting technique is called as raking or raking ratio estimation or rim or calibration weighting or multiplicative weighting. Here, it is defined as raking ratio estimation. In this model, correction weights are computed as the product of factors which is obtained by auxiliary information. If auxiliary variables are categorical, the raking ratio estimation technique is applied. This technique can also be utilized in the same situation of generalized regression modeling. Correction weight computation is an iterative procedure. The desired weights are the product of factors which is obtained by crossing the auxiliary variables in the target model.

Raking ratio estimation techniques were initially developed by Deming and Stephan (1940) to ensure that sample estimates provide consistent results to the population. This technique is matched sample and population characteristics only with respect to the marginal distributions of selected covariates, while post-stratification needs the joint distributions of the covariates, which is often not available for the population. This weighting can be conducted by an iterative algorithm to alternately adjust weights according to each covariates' marginal distribution until convergence. There are many algorithms for doing this. The one below was developed by Little and Wu (1991).

The following steps are needed for calculating the correct weight factors:

Step 1: By cross-classification in the model, introduce a weight factor for each stratum and put the initial values of all factors to 1.

Step 2: First cross-classification term is adjusted the weight factors to the weighted sample is turned into representative according to the auxiliary variables which involved in this cross-classification.

Step 3: The next cross-classification term is adjusted the weight factors so that the weighted sample is turned to representative of the involved variables.

Step 4: Iterate this adjustment procedure until all cross-classification terms will be met with.

Step 5: Iterate steps 2,3, and 4 until the weight factors do not deviate anymore.

Lee (2011) illustrated the above steps in following:

Consider two discrete covariates, with I and J levels, respectively, and suppose, the sample frequencies are arranged out in an $I \times J$ contingency table. Let n_{ij} be the cell count in i^{th} row and j^{th} column, n = total counts, and let w_i and w_j be the marginal target proportions of row i and column j in population, respectively

- Initialize the weights by setting each equal to $\widehat{w}_{ij}^{(0)} = \frac{n_{ij}}{n}$
- Raking over rows: $\widehat{w}_{ij}^{(1)} = w_i \times \frac{\widehat{w}_{ij}^{(0)}}{\sum_i w_i(0)}$
- Raking over columns: $\widehat{w}_{ij}^{(2)} = w_j \times \frac{\widehat{w}_{ij}^{(1)}}{\sum_i w_j(1)}$
- Repeat step 2 and 3 until $\sum_j w_{ij} = w_i$ and $\sum_i w_{ij} = w_j$ for each i and j, i.e., convergence achieves.

The study has three datasets which are large, for that reason, a suitable technical support is very necessary for performing analysis. Different software are utilized for computation the estimates. SPSS (version 22) has been used for analyzing the data. R programming has been utilized for simulation. XLSTAT has also been used for some analysis.

4. RESULTS AND INTERPRETATIONS

This section has explored the performance of the proposed weighting adjustment techniques for reducing the bias in the volunteer panel web survey. The objective of the adjustment techniques is to reduce the biases that may occur from the non-probability sampling design, non-response and under coverage problems. Here, to ensure vibrant findings, this study utilizes volunteer panel web sample, random sample (stratified), and population data as well as four weighting adjustment techniques—post-stratification weighting, generalized regression modeling, raking ratio estimation and propensity score adjustment. These four techniques have been compared to assess the degree of bias reduction. The volunteer panel web sample estimates have been compared with the random sample estimates as well. In the following text, the volunteer panel web survey analyses by implementing the four weighting adjustment techniques mentions in section 4.1, the analysis of the random sample data in the section 4.2, the bias reduction analyses in section 4.3, and finally, comparison of the performance of the estimates both the volunteer panel web survey and random sample data in section 4.4.

4.1. Analysis of the Volunteer Panel Web Survey Data by Weighting Adjusted Techniques

In this section, the study has been analyzed the volunteer panel web survey data by the proposed four weighting adjustment techniques for getting a more precise estimate which is shown below:

4.1.1. Analysis of the volunteer panel web survey data by post-stratification weighting adjustment technique

The first step of the analysis is to compare the percentage distribution of the response of the target variable with population distribution according to the selected auxiliary variables. It is shown as follows:

Table 4.1. *The percentage of using SNSs in the education for the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
	Frequency	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
No	429768	41.2	1255	43.0	+1.8
Yes	613515	58.8	1665	57.0	-1.8
Total	1043283	100	2920	100	

Table 4.1 evinces the overall using of social networking sites (SNSs) in the education of the population and volunteer panel web sample for the selected auxiliary variables. The volunteer panel web sample percentage (57.0%) of using the SNSs in the education is lower than the population percentage (58.8%) whereas not using the SNSs percentage (43.0%) is larger than the population percentage (41.2%). In the volunteer panel web sample, out of 2920 respondents, 1665 (57.0%) respondents use the SNSs in the education, but in the population, 613515 (58.8%) respondents consider the SNSs out of the1043283 respondents.

Table 4.2. *The percentage of using SNSs in the education for the gender in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Gender	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Male	362902	59.2	967	58.1	-1.1
Female	250613	40.8	698	41.9	+1.1
Total	613515	100	1665	100	

Table 4.2 represents the percentage distribution of the *Gender* variable. Female respondents are slightly overrepresented. Percentage differences in the volunteer panel web sample and population of the *Gender* variable are low. The positive sign of the difference between the population and sample percentage indicates overestimated and negative sign directs underestimated, and no difference suggests unbiased of estimates. Thus, male respondents are underrepresented, but female respondents are overrepresented.

Table 4.3. *The percentage of using SNSs in the education for the age in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Age (year)	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
<20	20490	3.3	58	3.5	+0.2
20-25	80130	13.1	542	32.6	+19.5
25-30	93987	15.3	449	27.0	+11.7
30-35	84132	13.7	239	14.4	+0.7
35-40	73872	12.0	126	7.6	-4.4
40-45	64059	10.4	88	5.3	-5.1
45^{+}	196845	32.1	163	9.8	-22.3
Total	613515	100	1665	100	

Table 4.3 compares the percentage of the volunteer panel web sample distribution of *Age* variable with its population distribution. Here, respondents in the age group 20-25 years' responses are the largest (32.6%) compared to other age groups, and it is overrepresented as well. The age group <20 years, 25-30 years, 30-35 years are overrepresented, but the age group 35-40 years, 40-45 years and 45^{+} years are underrepresented. Therefore, the responses of the *Age* variable are not good representation with respect to the age group.

Table 4.4. *The percentage of using SNSs in the education for the region in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Region	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference(%)**
Rural	45734	7.5	131	7.8	+0.3
Urban	267798	43.6	737	44.3	+0.7
Metropolitan	299983	48.9	797	47.9	-1
Total	613515	100	1665	100	

Table 4.4 demonstrates the regional comparison of the responses of the volunteer panel web survey and the population. The respondents who come from the urban and rural are slightly overrepresented, but the metropolitan area respondents are somewhat underrepresented.

Table 4.5. *The percentage of using SNSs in the education for the working status in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Working status	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Not-working	197997	32.3	542	32.6	+0.3
Part-time working	44571	7.3	141	8.5	+1.2
Full-time working	370947	60.5	982	59.0	-1.5
Total	613515	100	1665	100	

Table 4.5 shows the responses distribution of the target variable according to auxiliary variable the *Working status* and population distribution. Not-working and part-time working respondents are reasonably overrepresented, but full-time working respondents are slightly underrepresented.

Table 4.6. *The percentage of using SNSs in the education for marital status in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Marital status	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Single	354512	57.8	924	55.5	-2.3
Married	239765	39.1	678	40.7	+1.6
Divorced	15581	2.5	46	2.8	+0.3
Widowed	3657	0.6	17	1.0	+0.4
Total	613515	100	1665	100	

Table 4.6 denotes the percentage comparison of the volunteer panel web sample and population distribution with respect to the variable, *Marital status*. The respondents who are single are underrepresented, whereas, married, divorced and widowed respondents are overrepresented.

Table 4.7. *The percentage of using SNSs in the education for the level of program in the study of the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Level of program in the study	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Two-year associate degree	271550	44.3	757	45.5	+1.2
Four-year Bachelor's degree	341965	55.7	908	54.5	-1.2
Total	613515	100	1665	100	

Table 4.7 signifies the comparison of the variable, *Level of the program in the study,* between the volunteer panel web sample and population. Here, Four-year Bachelor's degree respondents are underrepresented, whereas two-year associate degree program respondents are overrepresented.

Table 4.8. *The percentage of using SNSs in the education for the faculty of study in the population and volunteer panel web sample*

	Population		Volunteer panel web sample		
Faculty in the study	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Open Education	549425	89.6	1406	84.4	-5.2
Economics	32528	5.3	140	8.4	+3.1
Business Administration	31562	5.1	119	7.1	+2.0
Total	613515	100	1665	100	

The percentage distribution of the variable, *Faculty in the study*, has been shown in Table 4.8. The volunteer panel web sample percentages of the target variable are compared to the population percentages according to the faculty categories. In some cases, the Open Education Faculty's respondents are underrepresented. The respondents, who are in Economics and Business Administration Faculties, are underrepresented. The volunteer panel web sample is not a proper representation with respect to the faculty levels.

Table 4.9. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the target variable*

	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate	Bias
No	0.9584535498	342.4446215139	429768(41.2%)	429768(41.2%)	0
Yes	1.0313157928	368.4774774775	613515(58.8%)	613515(58.8%)	0

Table 4.9 represents the post-stratification weights and adjustment weights for reducing the bias. It is noticeable that the bias of the estimate of the target variable in the volunteer panel web survey has completely removed.

Table 4.10. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the gender*

Gender	Weight	Adjustment weight for sample	Post-stratification weighted estimate for sample	Population estimate	Bias
Male	1.0184786748	375.2864529473	362902 (59.2%)	362902 (59.2%)	0
Female	0.9743998875	359.0444126074	250613 (40.8%)	250613(40.8%)	0

Table 4.10 shows the post-stratification weight and adjustment weight for reducing the bias of the estimate of the *Gender* variable. The response percentage (58.1%) of male respondents is lower than the population percentage (59.2%) which has shown in Table 4.2. Thus, post-stratification allots a weight which is higher than one, whereas the post-stratification weight for female respondents are lower than one. The weight for male (1.0184786748) is the ratio of the population percentage to the sample percentage. Similarly, for the female is 0.9743998875, because the sample percentage (41.9%) of female is higher than the population percentage (40.8%). Thus, the weight is lower than 1. After adjusting the weight, we observe that there is no bias in the *Gender* variable.

In this way, we can compute the post-stratification weight and adjusted weight for reducing the bias of the estimate for all selected auxiliary variables which are as follows:

Table 4.11. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample for the age*

Age (year)	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
<20	0.9587447908	353.275862069	20490(3.3%)	20490(3.3%)
20-25	0.4012221573	147.841328133	80130(13.1%)	80130(13.1%)
25-30	0.5680813071	209.3251670379	93987(15.3%)	93987(15.3%)
30-35	0.9553276874	352.0167364017	84132(13.7%)	84132(13.7%)
35-40	1.5911032563	586.2857142857	73872(12.0%)	73872 (12.0%)
40-45	1.9755432185	727.9431181882	64059(10.4%)	64059(10.4%)
45^+	3.2773727314	1207.6380368098	196845(32.1%)	196845(32.1%)

Table 4.12. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the region*

Region	Weight	Adjustment weight for sample	Poststratification weighted estimate for the sample	Population estimate
Rural	0.9474514052	349.11455038168	45734 (7.5%)	45734(7.5%)
Urban	0.9861180173	363.3622795115	267798 (43.6%)	267798(43.6%)
Metropolitan	1.021474137	376.3902132999	299983 (48.9%)	299983(48.9%)

Table 4.13. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the working status*

Working status	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Not-working	0.9913987704	365.3081180812	197997(32.3%)	197997(32.3%)
Part-time working	0.8578716538	316.1063829787	44571(7.3%)	44571(7.3%)
Full-time working	1.0251547488	377.7464358452	370947(60.5%)	370947(60.5%)

Table 4.14. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the marital status*

Marital status	Weight	Adjustment weight for sample	Poststratification weighted estimate for the sample	Population estimate
Single	1.0412332344	383.670995671	354512(57.8%)	354512(57.8%)
Married	0.9597213258	353.6356932153	239765(39.1%)	239765(39.1%)
Divorced	0.9192349927	338.7173913043	15581(2.5%)	15581(2.5%)
Widowed	0.5838013453	215.1176470588	3657(0.6%)	3657(0.6%)

Table 4.15. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the level of the program in the study*

Level of program in the study	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Two-year associate degree	0.9735157454	358.7186261559	271550(44.3%)	271550(44.3%)
Four-year Bachelor's degree	1.0220799347	376.6134361233	341965(55.7%)	341965(55.7%)

Table 4.16. *Computing the post-stratification weights and adjustment weights for reducing the bias of the volunteer panel web sample estimate for the faculty in the study*

Faculty in the study	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Open Education	1.0605036037	390.7716927454	549425(89.6%)	549425(89.6%)
Economics	0.6305483275	232.3428571429	32528(5.3%)	32528(5.3%)
Business Administration	0.7197913223	265.2268907563	31562(5.1%)	31562(5.1%)

Table 4.11, Table 4.12, Table 4.13, Table 4.14, Table 4.15, and Table 4.16 represents the post-stratification and adjustment weighting for reducing the bias of the variables: *Age, Region, Working status, Marital status, Level of the program in the study and Faculty in study*.

The adjustment weights w_i is the product of the correction weights c_i and the inclusion weights d_i. It calculates as $d_i = N/n$. The inclusion weight is equal to N/n = 613515/1665 = 368.4774774775 which is same for all selected auxiliary variables. Suppose that the weights are used to estimate the number of male respondents in the population. The weighted estimate would be $c_i \times d_i \times n_h$=1.0184786748 × 368.4774774775×967=362902, and it is exactly the number of the male respondents of the population. Therefore, the bias has completely removed.

Similarly, the study can estimate the target variable of the volunteer panel web sample using the auxiliary variables as a weight. Thus, the application of the post-stratification weights to the auxiliary variables estimates accurately. If there is a strong relationship between the auxiliary variables and the target variable (s), estimates of the target variable will be improved by using the auxiliary variables as a weight. The post-stratification weighting technique has been implemented to the volunteer panel web sample data for reducing the bias of the estimate of the target variable.

4.1.2. Estimation of the target variable by post-stratification weighting for the volunteer panel web survey

The post-stratification weighting adjustment technique has examined the non-response bias of the estimate. The demographic characteristics (*Gender, Age, Region, Working status, Marital status, Level of the program in the study and Faculty in the study)* are used as auxiliary variables. The post-stratification weighting adjustment is successful which is shown in section 4.1. The bias has completely removed from estimate for all the auxiliary variables. Now, the study will examine whether the estimate of the target variable reduces the bias.

Now, it explores how above mentioned auxiliary variables can use for weighting adjustment. In the volunteer panel web survey, the target variable is the "*using social networking sites in the education"* where the volunteer panel web response percentage of the using SNSs in the education is 57.00% and the population percentage of the individuals using SNSs in the education is 58.80%. The difference between the volunteer panel web sample estimate and population estimate is significantly different—i.e., 1.88%. Therefore, the volunteer panel web sample estimate is a biased estimate. Now, the study examines whether this estimate can be improved by weighting adjustment. It considers seven weighting models which are statistically significant. These weighting models have been created by using above mentioned auxiliary variables.

Table 4.17. *Post-stratification weighting estimation of the target variable for reducing the bias in the volunteer panel web survey*

Weighting model	Estimate (%)	Standard error
No weighting	**57.00**	**0.9160**
1. Gender	56.87	0.9667
2. Age	56.51	1.2217
3. Region	57.02	0.9156
4. Working status	57.04	0.9155
5. Marital status	57.02	0.8961
6. Level of the program in the study	**58.87**	**0.9025**
7. Faculty in the study	57.05	0.9244
Population	**58.80**	

Table 4.17 illustrates the post-stratification estimates of the target variable *"using social networking sites in the education"* to the weighting models with its standard error. There is almost no change in the estimate, and no reduction in the standard error of the estimate. For that reason, most of the weighting model's effects are not acceptable. The result is different in the model-6 for the variable of *Level of the program in the study*. The estimate of the model-6 has adjusted in correction, from 58.80% to 58.87%. The standard error of the adjusted estimate (0.9025) is also lower than unadjusted estimate. Therefore, the post-stratification estimate is almost unbiased for the variable, *Level of the program in the study*. It is recommended that the variable may be included in the post-stratification weighting model for reducing the bias in the volunteer panel web sample estimate.

4.1.3. Analysis of the volunteer panel web survey data by generalized regression modeling

The generalized regression model's estimates—based on a linear model—explain a target variable of the volunteer panel web survey from auxiliary variables. These estimates are not only capable of producing precise estimates, but it also can reduce the bias of those estimates. It denotes that the generalized regression modeling, in fact, is a form of weighting like post-stratification weighting and can prove that post-stratification is a special case of linear weighting. In theory, it has been mentioned in the above text that the use of the generalized regression model provides the potential bias reduction estimates which are resulting from the self-selection problem.

The study has utilized the volunteer panel web survey data. The objective of the survey is to estimate the "*using social networking sites in the education*". A volunteer panel web survey by self-selection sample has been collected from 1043283 respondents of Open Education System, Anadolu University. The volunteer panel web sample size is 2920 and have seven auxiliary variables. A set of dummy variables has been created by using the selected seven auxiliary variables which compute weights considering only their marginal distributions. Seventeen weighting models has been implemented in the generalized regression modeling.

Table 4.18. *Generalized regression estimation of the target variable for reducing the bias in the volunteer panel web survey.*

Weighting model	Estimate (%)	Standard error (%)
No weighting	**57.00**	**0.915**
1. Gender	57.42	1.205
2. Age	56.66	0.584
3. Region	57.24	0.775
4. Working status	57.83	0.819
5. Marital status	57.61	1.310
6. Level of program in the study	56.54	1.238
7. Faculty in the study	56.00	1.912
8. Gender × Age	58.61	0.753
9. Gender × Region	57.53	1.029
10. Gender × Working status	**58.80**	**0.998**
11. Gender × Marital status	57.40	1.759
12. Age ×Working Status	**58.83**	**0.505**
13. Age × marital status	58.30	0.745
14. Gender × Age ×Working status	59.05	0.610
15. Gender + Age +Working status	57.40	0.442
16. Gender × Age × Region × Working status × Marital status × Level of program in the study × Faculty in the study	71.14	1.522
17. Gender + Age + Region + Working status +Marital status + Level of program in the study +Faculty in the study	57.40	0.347
Population	**58.80**	

Table 4.18 represents the generalized regression estimation for different weighting models for reducing the bias. The population percentage of the "*using social networking sites in the education"* is 58.80% and the volunteer panel web sample estimate of the target variable is 57.00%. Therefore, the estimate of the unadjusted weighting model (no weighting) is biased. This estimate has a substantial downward bias which is not surprising because respondents with a participation probability also are less inclined to the *using social networking sites in the education*. The weighting effects are low for most of the single variable weighting models. There is almost no change in the estimate, but there is a small reduction of the standard error in some weighting models, and other weighting models also have increased standard errors. In weighting model-1, model-2, model-3, model-4, model-5, model-6, model-7, model-8, model-9, model-11, model-13, model-14, model-15, model-16, and model-17, the bias reduction is somewhat but not completely removed. Model-12 depicts that the estimate is almost same to the population parameter, and its standard error is lower than other weighting models. The model-10 (*Gender* × *Working status*) shows that the volunteer panel web sample estimate is precisely equal to the population estimate. This estimate is unbiased. For this weighting model-10, the bias has removed totally. Therefore, in the generalized regression modeling, the weighting model-10 should be used for reducing the bias in the volunteer panel web sample estimate.

4.1.4. Analysis of the volunteer panel web survey data by raking ratio estimation

Generalized regression modeling is applied if there is a linear relationship between the target variable(s) and auxiliary variables, but the raking ratio technique is used when that relation is a log-linear. In an application of the generalized regression modeling, the correction weights are obtained by taking the sum of weight coefficients. But, in the raking ratio estimation, correction weights are found by taking the product of the weight factors. This weighting technique is typically known as raking ratio estimation, or raking, or multiplicative weighting. Here, in the study, it is denoted by raking ratio estimation. Raking ratio estimation techniques was developed initially by Deming and Stephan (1940). In raking ratio estimation, seventeen weighting models have been implemented to get the precise estimates of the volunteer panel web sample.

Table 4.19. *Raking ratio estimation of the target variable for reducing the bias in the volunteer panel web survey*

Weighting model	Estimate (%)	Standard error (%)
No weighting	**57.00**	**0.915**
1. Gender × Working status	58.58	0.913
2. Gender ×Working status ×Level of program in the study	58.24	0.913
3. Gender ×Working status ×Level of program in the study ×Region	58.33	0.913
4. Gender ×Working status ×Level of program in the study ×Region ×Age	58.61	0.912
5. Gender ×Working status ×Level of program in the study × Age	**58.82**	**0.907**
6. Gender ×Working status × Age	58.52	0.912
7. Gender ×Working status × Age ×Faculty in the study	58.60	0.906
Population	**58.80**	

Table 4.19 shows the target variable estimate of different weighting models with its standard error. In weighting model-1, model-2, model-3, model-4, model-6, and model-7, the bias reduction is well but not completely removed. On the other hand, the weighting model-5 signifies that the estimate of the volunteer panel web sample is almost equal to the population estimate and its standard error is less than the unadjusted estimate. The estimate of the weighting model-5 should be considered the parameter estimate in the raking ratio estimation technique. Therefore, raking ratio estimation technique can be reduced the bias of the volunteer panel web sample estimate.

4.1.5. Analysis of the volunteer panel web survey data by PSA

PSA technique has been used for the non-response bias. In this case, MAR has been considered as non-response, logit regression model has been used for computing the propensity score adjustment, and inverse propensity has been used as weight for reducing the nonresponse bias. Importantly, only significant eight weighting models have been utilized in the PSA.

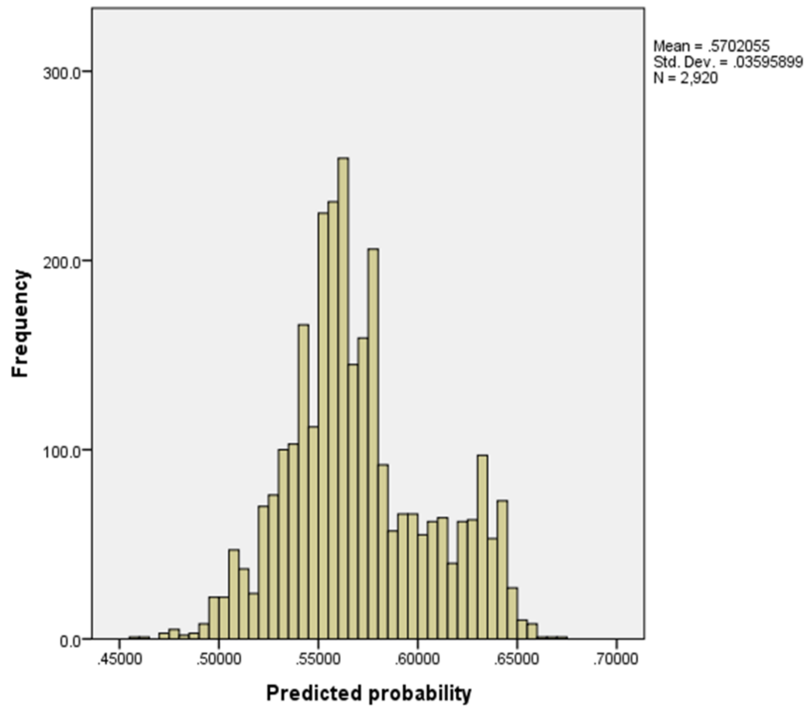

Figure 4.1. *Propensity score for using SNSs in the education*

After calculating propensity scores, the PSA weights have been computed in each model by the inverse of propensity scores as weights. In the inverse propensity score weights, when the probability of "web individuals' is negligible, the weight will be huge. Therefore, the weights may be affected substantially by propensity score models or properties of the data. Figure 4.1 and Figure 4.2 illustrate the distribution of the propensity score and propensity score weights of the unadjusted model respectively. The mean propensity score of the target variable is 0.57. This means that the average probability of using social networking sites in the education is 57% and standard deviation is 0.0360. The minimum proportion of using social networking sites in the education is almost 46%, and the maximum percentage is approximate 68. The average inverse propensity score weight is 1.7607 and its standard deviation is 0.10977.

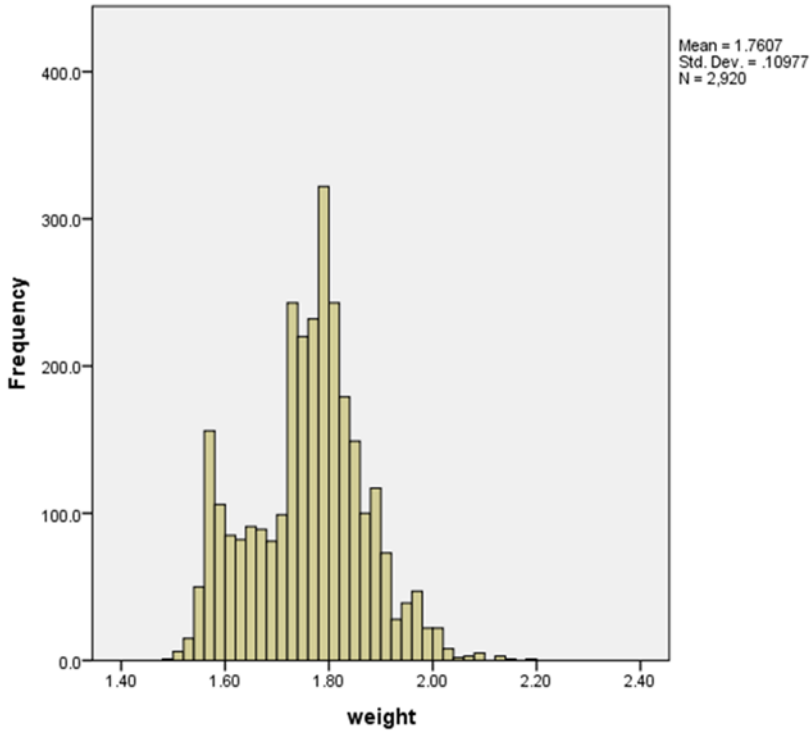

Figure 4.2. *Distribution of PSA weights based on inverse propensity score weights for the unweighted model*

Table 4.20. *Propensity score adjustment estimation of the target variable for reducing the bias of the volunteer panel web survey*

Weighting model	**Estimate (%)**	**Standard error (%)**
No weighting	**57.00**	**0.915**
1. Gender	57.20	0.912
2. Working status	57.10	0.911
3. Gender × Working status	**57.98**	**0.692**
4. Gender ×Working status ×Level of program in the study	57.96	0.613
5. Gender ×Working status ×Level of program in the study ×Region	**57.98**	**0.613**
6. Gender ×Working status ×Level of program in the study × Region ×Age	57.61	0.612
7. Gender ×Working status ×Level of program in the study × Age	56.82%	0.907
8. Gender ×Working status × Age	57.52%	0.912
Population	**58.80**	

Table 4.20 represents the volunteer panel web sample estimate of the target variable. The weighting correction performance of the weighting model-3, and model-5 is better than model-1, model-2, model-4, model-6, model-7, and model-8. Almost all weighting models reduce some bias but not completely. At the same time, it has reduced standard error of the estimate. In the PSA technique, weighting model-3 or model-5 should be used for reducing the bias of the volunteer panel web sample estimate.

4.2. Analysis of the Random Sample Data by Weighting Adjusted Techniques

The analysis of the random sample data by four weighting adjustment techniques which has been applied in the volunteer panel web sample analysis are as follows:

4.2.1. Post-stratification weighting adjusted technique for the random sample data

The first step of the analysis is to compare the random sample distribution with the population distribution according to the selected auxiliary variables. The following tables represent the random sample distribution with its population distribution:

Table 4.21. *The percentage of using the SNSs in the education for the population and random sample*

	Population		Random sample		
	Frequency	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
No	429768	41.2	985	41.1	-0.10
Yes	613515	58.8	1411	58.9	+0.10
Total	1043283	100	2396	100	

Table 4.21 shows the overall using SNSs in the education of the population and random sample for the selected variables. The random sample percentage (58.9%) of using SNSs in the education is higher than the population percentage (58.8%) whereas not using of SNSs of random sample percentage (41.1%) is lower than the population percentage (41.2%). In the random sample, out of 2396 respondents, 1411 (58.9%) respondents use the SNSs in education. But, in the population, 613515 (58.8%) respondents use SNSs out of 1043283 individuals. Therefore, the using SNSs in the education is overrepresented, but not using SNSs in the education is underrepresented.

Table 4.22. *The percentage of using SNSs in the education of the population and random sample for the gender*

	Population		Random sample		
Gender	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Male	362902	59.2	840	59.5	+0.30
Female	250613	40.8	571	40.5	-0.30
Total	613515	100	1411	100	

Table 4.22 indicates the gender variable distribution. Female respondents are slightly underrepresented, whereas the male respondents are somewhat overrepresented. Percentage differences between the sample and population of the *Gender* variable are less. The positive sign of the difference between population and sample percentage indicates overestimated, and the negative sign directs underestimated, and no difference indicates unbiased estimate. This implies that the estimate of the variable, *Gender,* is biased.

Table 4.23. *The percentage of using SNSs in the education of the population and random sample for the age*

	Population		Random sample		
Age (year)	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference(%)**
<20	20490	3.3	45	3.2	-0.10
20-25	80130	13.1	171	12.1	-1
25-30	93987	15.3	208	14.7	-0.60
30-35	84132	13.7	199	14.1	0.40
35-40	73872	12.0	158	11.2	-0.80
40-45	64059	10.4	150	10.6	+0.20
45^{+}	196845	32.1	480	34.0	+1.90
Total	613515	100	1411	100	

Table 4.23 compares the random sample distribution of the variable, *Age,* with its population distribution. Respondents in the age group 45^{+} years is the maximum (34%) response rate compared to other age groups, and it is overrepresented. Likewise, the age 40-45 years are also overrepresented. On the other hand, age group <20 years, 20-25 years, 25-30 years, and 35-40 years are underrepresented.

Table 4.24. *The percentage of using SNSs in the education of the population and random sample for the region*

	Population		Random sample		
Region	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Rural	45734	7.5	92	6.5	-1
Urban	267798	43.6	606	42.9	-0.7
Metropolitan	299983	48.9	713	50.5	+1.60
Total	613515	100	1411	100	

Table 4.24 represents the percentage distribution of the *Region* of the random sample and population. The respondents come from the rural and urban are slightly underrepresented, but the metropolitan area respondents are overrepresented.

Table 4.25. *The percentage of using SNSs in the education of the population and random sample for the working status*

	Population		Random sample		
Working status	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference(%)**
Not-working	197997	32.3	448	31.8	-0.50
Part-time working	44571	7.2	104	7.4	+0.20
Full-time working	370947	60.5	859	60.8	+0.30
Total	613515	100	1411	100	

Table 4.25 denotes the random sample and population percentage distribution of the *Working status*. Full-time working and part-time working respondents are overrepresented, but not-working respondents are slightly underrepresented.

Table 4.26. *The percentage of using SNSs in the education of the population and random sample for the marital status*

	Population		Random sample		
Marital status	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Single	354512	57.8	842	59.7	+1.90%
Married	239765	39.1	524	37.1	-2
Divorced	15581	2.5	34	2.4	-0.10
Widowed	3657	0.6	11	0.8	+0.20
Total	613515	100	1411	100	

Table 4.26 illustrates the comparison of the random sample of the *Marital status* with population distribution. Respondents who are single and widowed are overrepresented, whereas married and divorced respondents are underrepresented.

Table 4.27. *The percentage of using SNSs in the education of the population and random sample for the level of program in the study*

	Population		Random sample		
Level of program in the study	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Two-year associate degree	271550	44.3	632	44.8	+0.50
Four-year Bachelor's degree	341965	55.7	779	55.2	-0.50
Total	613515	100	1411	100	

Table 4.27 shows the percentage distribution of the random sample and population of the *Level of the program in the study*. Four-year Bachelor's degree students' response (55.2%) is higher than the students who are studying in the two-year associate degree program (44.8%). The two-year associate degree program respondents are overrepresented, but the respondents of the Four-year Bachelor's degree program are underrepresented.

Table 4.28. *The percentage of SNSs in the education of the population and random sample for the faculty in the study*

	Population		Random sample		
Faculty in the study	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**	**Difference (%)**
Open Education	549425	89.6	713	50.5	-39.10
Economics	32528	5.3	360	25.5	+20.20
Business Administration	31562	5.1	338	24.0	+18.90
Total	613515	100		100	

The percentage distribution of the random sample and population for the *Faculty in the study* has been shown in Table 4.28. The Open Education Faculty's respondents are underrepresented, whereas the Economics and Business Administration Faculty's respondents are overrepresented. The difference of the percentage between the population and random sample estimate is large. Therefore, it can be concluded that the random sample is not a good representation compared to the *Faculty in the study*.

Table 4.29. *Computing the post-stratification weights and adjustment weights for reducing the bias of the random sample estimate for the gender*

Gender	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate	Bias
Male	0.9936007347	432.0261904762	362902(59.2%)	362902(59.2%)	0
Female	1.1148460016	484.7446808511	250613(40.8%)	250613(40.8%)	0

The post-stratification weight and adjustment weight for reducing the bias of the random sample estimate of the *Gender* has been illustrated in Table 4.29. The weight for male respondents is obtained by dividing the population percentage to the random sample percentage which is 0.9936007347. Similarly, for the female is 1.114860016. After adjusting the weight, it has observed that there is no bias of the random sample estimate for the *Gender*.

Similarly, we can compute the post-stratification weight and adjusted weight to reduce the bias of the random sample estimate of the target variable for implementing weighting models. The study has observed that there is no bias in the estimate after implementing the post-stratification weighting technique.

Table 4.30. *Computing the post-stratification weights and adjustment weights for reducing the bias of the random sample estimate for the age*

Age (year)	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
<20	1.0472039532	455.3333333333	20490(3.3%)	20490(3.3%)
20-25	1.0777073896	468.5964912281	80130(13.1%)	80130(13.1%)
25-30	1.0392170917	451.8605769231	93987(15.3%)	93987(15.3%)
30-35	0.9723216705	422.7738693467	84132(13.7%)	84132(`3.7%)
35-40	1.0752875034	467.5443037975	73872(12.0%)	73872(12.0%)
40-45	0.9821791806	427,0600000000	64059(10.4%)	64059(10.4%)
45^{+}	0.9431591424	410.0937500000	196845(32.1%)	196845(32.1%)

Table 4.31. *Computing the post-stratification weights and adjustment weights for reducing the bias of the random sample estimate for the region*

Region	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Rural	1.14322815328	497.1086956522	45734(7.5%)	45734(7.5%)
Urban	1.0163341847	441.9108910891	267798(43.6%)	267798(43.6%)
Metropolitan	0.9676291487	420.7335203366	299983(48.9%)	299983(48.9%)

Table 4.32. *Computing the post-stratification weights and adjustment weights for reducing bias of the random sample estimate for the working status*

Working status	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Not-working	1.0164415841	441.9575892857	197997(32.3%)	197997(32.3%)
Part-time working	0.9856457807	428.5673076923	44571(7.2%)	44571(7.2%)
Full-time working	0.9931629908	431.8358556461	370947(60.5%)	370947(60.5%)

Table 4.33. *Computing the post-stratification weights and adjustment weights for reducing the bias of the random sample estimate for the marital status*

Marital status	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Single	0.9683239581	421.0356294537	354512(57.8%)	354512(57.8%)
Married	1.0523406048	457.5667938931	239765(39.1%)	239765(39.1%)
Divorced	1.0539457063	458.2647058824	15581(2.5%)	15581(2.5%
Widowed	0.7645996653	332.4545454545	3657(0.6%)	3657)0.6%)

Table 4.34. *Computing the post-stratification weights and adjustment* weights for reducing the bias of the random sample estimate for the level of the program in the study

Level of program in the study	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Two-year associate degree	0.988176581	429.667721519	271550(44.3%)	271550(44.3%)
Four-year Bachelor's degree	1.0095922989	438.9794608472	341965(55.7%)	341965(55.7%)

Table 4.35. *Computing the post-stratification weights and adjustment weights for reducing the bias of the random sample estimate for the faculty in the study*

Faculty in the study	Weight	Adjustment weight for sample	Post-stratification weighted estimate for the sample	Population estimate
Open Education	1.7722325767	770.5820476858	549425(89.6%)	549425(89.6%)
Economics	0.207805333	90.3555555556	32528(5.3%)	32528(5.3%)
Business Administration	0.2147581448	93.3786982249	31562(5.1%)	31562(5.1%)

Table 4.30, Table 4.31, Table 4.32, Table 4.33, Table 4.34, and Table 4.35 evince the post-stratification weight and adjustment weight for reducing the bias of the random sample estimate for the selected auxiliary variables—*Age, Region, Working status, Marital status, Level of the program in the study and Faculty in the study*—respectively. It has observed for all the selected auxiliary variables that after adjusting the weight, the post-stratification weighted estimate for the random sample is exactly equal to the population estimate. Thus, the post-stratification weighting adjustment technique is

effective here. Therefore, the bias of the random sample estimate has completely removed for all selected auxiliary variables.

Similarly, we can compute the random sample estimate of the target variable by post-stratification weighting technique. This estimation is shown below:

4.2.2. Estimation of target variable by post-stratification weighting for the random sample

Here, the target variable is: *"using social networking sites in the education"*. The variable's random sample estimate is 58.90% and population estimate is 58.80%. The difference between the random sample estimate and population estimate is significantly minimal, i.e., 0.10%. Thus, the random sample estimate is a biased estimate. For that reason, the post-stratification weighting technique can utilize to reduce the bias of the random sample estimate of the target variable.

Table 4.36. *Post-stratification weighting estimation of the target variable for reducing the bias in the random sample*

Weighting model	Estimate (%)	Standard error
No weighting	**58.90**	**1.0000**
1. Gender	58.88	1.0094
2. Age	58.97	0.9475
3. Region	58.91	1.0069
4. Working status	**58.81**	**0.9500**
5. Marital status	58.89	0.6948
6. Level of program in the study	**58.83**	**1.0045**
7. Faculty in the study	58.91	1.2745
Population	**58.80**	

Table 4.36 shows the post-stratification estimates of the target variable according to the implemented weighting models and standard errors of the estimates of the models. The effects of the weighting models are significant for some auxiliary variables. There is a significant amount of change in the estimate and standard error after adjusting the weights. This change is positive for the model-4 and model-6 which have been created

by the *Marital status* and *Level of the program in the study* respectively. These model's estimates have adjusted in correction, from 58.80% to 58.81% for the model-4 and from 58.80% to 58.83% for the model-6. The standard errors of the adjusted estimate of model-4 is also reduced. Therefore, the post-stratification estimates of the target variable of the random sample are almost unbiased for the model-4 (*Marital status*) and model-6 (*Level of the program in the study*). It can be said that the model-4 and model-6 should be used for reducing the bias of the random sample estimate.

4.2.3. Estimation of the target variable by generalized regression modeling for the random sample

In generalized regression modelling, seventeen weighting models have been created by crossing or adding the selected auxiliary variables in the study and computed the weighting considering only their marginal distributions. The distribution of different estimates of the implemented weighting models are compared below:

Table 4.37. *Generalized regression estimation of the target variable for reducing the bias in the random sample*

Weighting model	Estimate (%)	Standard error (%)
No weighting	**58.90**	**1.00**
1. Gender	59.00	1.30
2. Age	58.20	0.50
3. Region	59.00	0.70
4. Working status	59.00	0.70
5. Marital status	58.10	0.80
6. Level of program	59.00	1.40
7. Faculty in the study	59.00	0.80
8. Gender × Age	**58.90**	**0.70**
9. Gender ×Region	59.00	0.80
10. Gender × Working status	**58.80**	**0.90**
11. Gender × Marital status	58.00	1.10
12. Age ×Working Status	58.00	0.30
13. Age × marital status	58.30	0.40
14. Gender × Age ×Working status	59.00	0.40
15. Gender + Age +Working status	59.00	0.40

Table 4.37. (Continued) *Generalized regression estimation of the target variable for reducing the bias in the random sample*

16. Gender × Age × Region × Working status × Marital status × Level of program × Faculty of study	57.00	0.20
17. Gender + Age + Region + Working status +Marital status + Level of program +Faculty of study	59.00	0.30
Population	**58.80**	

Generalized regression estimation of target variable for reducing the bias in the random sample has been exhibited in Table 4.37. The weighting effects are less for most of the weighting models. There is almost no change in the adjusted estimate, but some reduction is in the standard error. In the weighting model-1, model-3, model-4, model-5, model-7, model-8, model-9, model-14, model-15, and model-17, there is no change in the estimate, but the model-2, model-5, model-11, model-12 and model-16 have reduced some degree of bias of the random sample estimate. The model-10 (*Gender × Working status*) has observed that the random sample estimate (proportion) is exactly equal to the population estimate. Thus, the estimate is unbiased. Along with, the weighting model-10 may be used for estimating the random sample estimate. Therefore, generalized regression modeling technique has totally reduced the bias of the random sample estimate.

4.2.4. Analysis of the random sample data by raking ratio estimation

This method is to explore whether the weighting model can improve by crossing at least two auxiliary variables. In this analysis, seven weighing models have been created for reducing bias in the random sample estimate of the target variable and these created models are statistically significant. The raking ratio estimation table is given below:

Table 4.38. *Raking ratio estimation of the target variable for reducing the bias in the random sample*

Weighting model	Estimate (%)	Standard error (%)
No weighting	**58.90**	**1.00**
1. Gender × Working status	**58.75**	**1.60**
2. Gender ×Working status ×Level of program in the study	58.00	1.60
3. Gender ×Working status ×Level of program in the study ×Region	58.20	2.70
4. Gender ×Working status ×Level of program in the study ×Region ×Age	58.20	2.70
5. Gender ×Working status ×Level of program in the study × Age	60.00	1.10
6. Gender ×Working status × Age	58.00	1.00
7. Gender ×Working status × Age ×Faculty in the study	58.00	1.30
Population	**58.80**	

Table 4.38 shows the raking ratio estimation of the target variable for reducing the bias in the random sample. After adjusted the raking weight, there has no significant change occurs in the random sample estimate, but standard errors have been increased in the implemented weighting models. Therefore, we may conclude that the raking ratio estimation of the random sample data is not significantly efficient for reducing the bias except the model-1 (*Gender × Working status*).

4.2.5. Analysis of the random sample data by PSA

The propensity score has been computed by logit model. Eight weighting models have been created for the propensity score adjustment technique. After calculating the propensity scores, the PSA weights have been computed in each model by the inverse of propensity scores as weights. The propensity scores show in Figure 4.3, and propensity score inverse weights represent in Figure 4.4. The mean propensity score of the target variable is 0.5888982 which indicates that the usage of the SNSs in the education is 58.89% and its standard deviation is 0.03363743. The average inverse propensity score adjustment for the target variable is 1.7037, and its standard deviation is 0.09793.

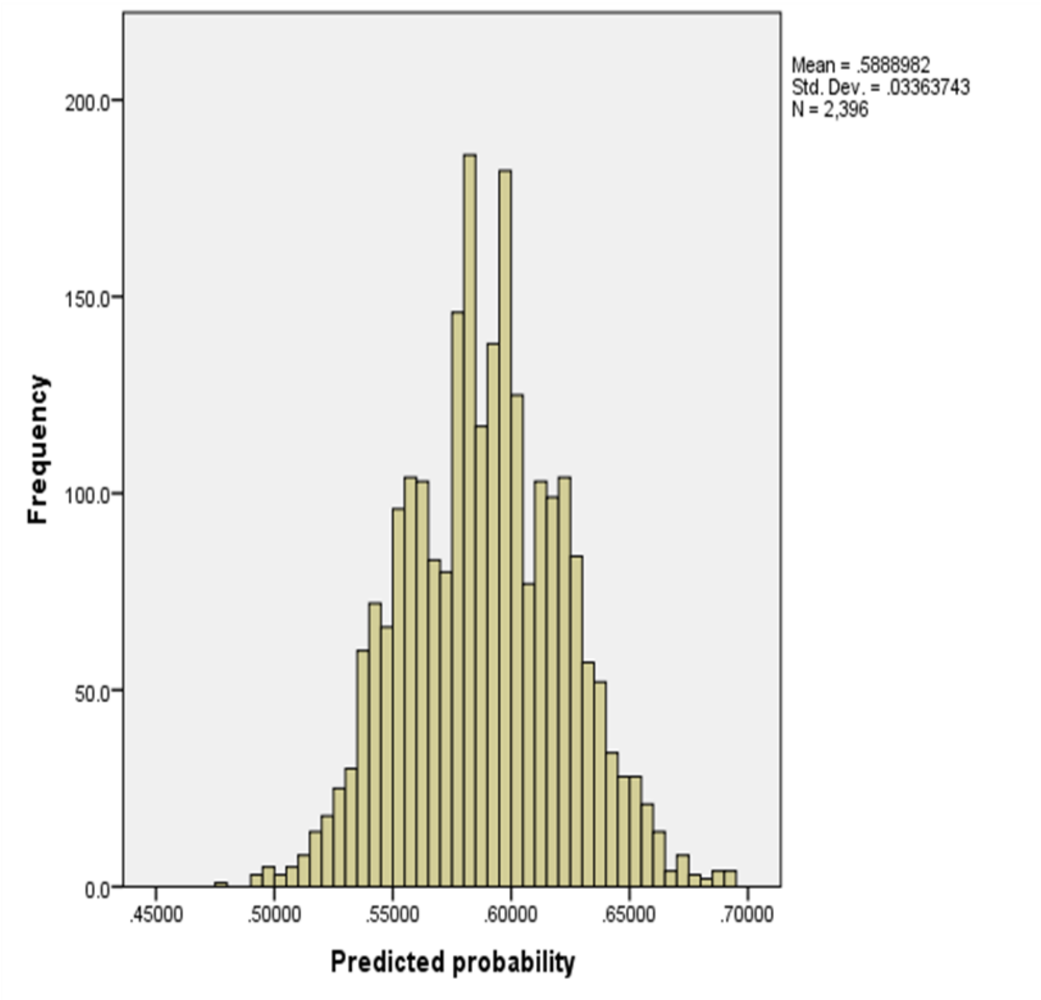

Figure 4.3. *Distribution of propensity score of the target variable*

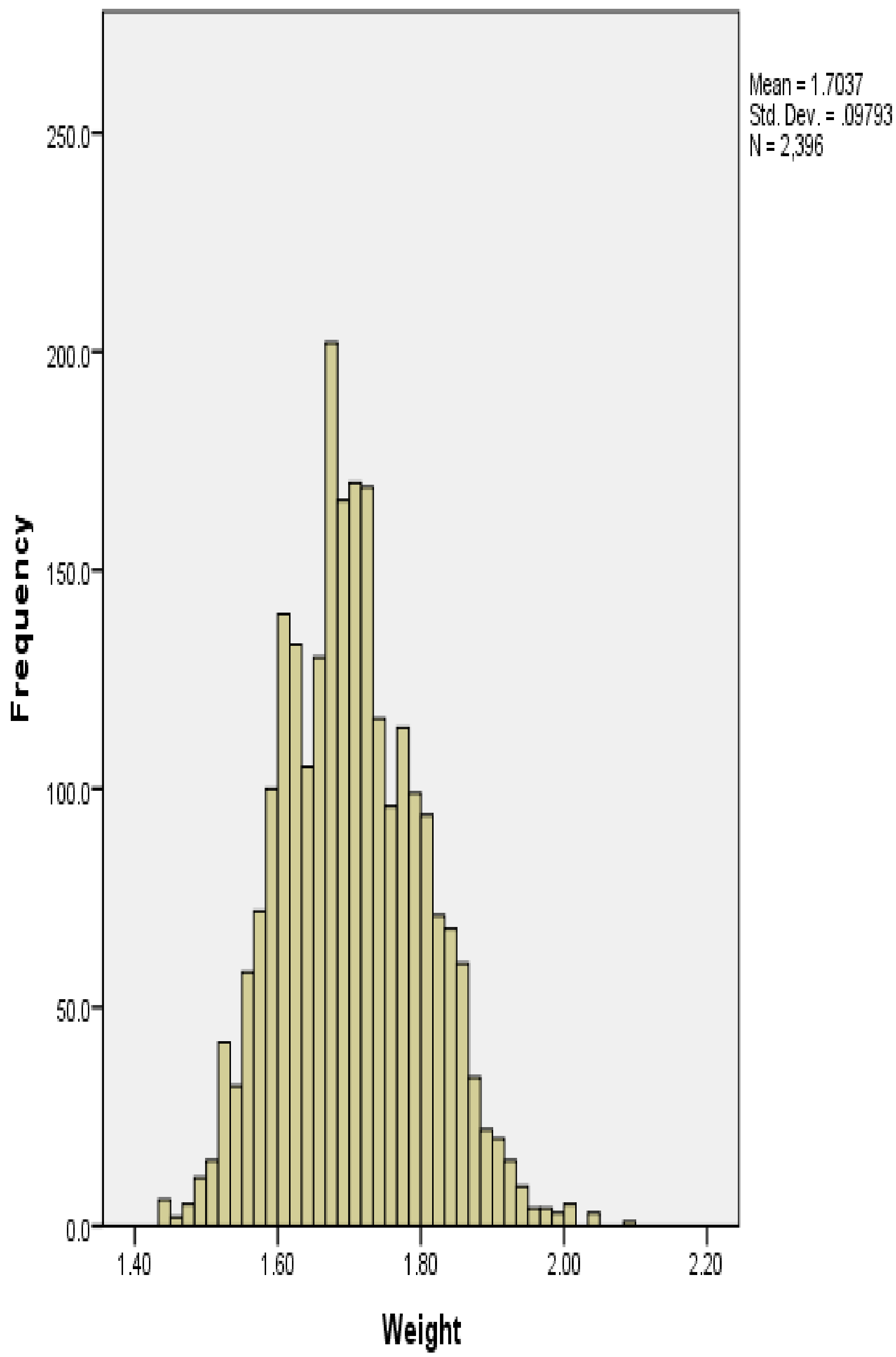

Figure 4.4. *Distribution of PSA weights based on inverse propensity score weights in the unweighted model*

Table 4.39. *PSA estimation of the target variable for reducing the bias in the random sample*

Weighting model	Estimate (%)	Standard error (%)
No weighting	**58.90**	**1.00**
1. Gender	**58.72**	**0.812**
2. Working status	58.70	0.811
3. Gender × Working status	**58.77**	**0.692**
4. Gender ×Working status ×Level of program in the study	58.96	0.713
5. Gender ×Working status ×Level of program in the study ×Region	58.98	0.713
6. Gender ×Working status ×Level of program in the study ×Region ×Age	59.00	0.912
7. Gender ×Working status ×Level of program in the study × Age	**58.82**	**0.807**
8. Gender ×Working status × Age	58.52	0.912
Population	**58.80**	

Table 4.39 demonstrates the PSA estimation of the target variable for reducing the bias in the random sample including its standard error. The model-1, model-3, and model-7 have reduced the bias significantly whereas the model-2, model-4, model-5, and model-8 have no significant reduction of the bias after adjusting the PSA weights. The estimate of the model-7 is almost equal to the parameter value. Therefore, model-7 should be used for reducing the bias of the random sample estimate for the PSA technique.

4.3. Bias Reduction

Theoretically, a good estimator does not guarantee the bias reduction of an estimate in the sample because survey weights and application of adjustment have not been performed yet. Thus, the primary attention is on the performance of each implemented techniques according to the percentage of bias reduction. The study has been considered four different weighting adjustment techniques. In each technique, there have different weighting models.

Each of the weightings models is assessed based on the target variable in terms of the percentage bias reduction. The computation of percentage bias reduction formula (Lee, 2011) is defined as follow:

$$p.bias(\hat{\theta}^{W.A)} = \left[\frac{|bias(\hat{\theta}W.U)| - |bias(\hat{\theta}W.A)|}{|bias(\hat{\theta}W.U)|}\right] \times 100 \quad (4.1)$$

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

The study has the parameter value, the volunteer panel web sample, and random sample estimates based on the implemented weighting models. The percentage bias reduction of each weighting model has been computed for mentioned weighting adjustment techniques. A large percentage reduction bias indicates that the adjustment has reduced more biases. It measures the bias in adjusted estimates relative to unadjusted estimate which is expressed as percentage. The negative percentage bias reduction means that the adjusted bias has become worse. The ANOVA has been performed to conclude which weighting model has reduced the best bias among the all selected models. Now, only significant weighing models' bias reduction has been shown following:

4.3.1. Percentage bias reduction for the volunteer panel web survey

In this section, the primary consideration is the performance of the estimates of the weighting models which is determined by the percentage bias reduction. A significant percentage reduction means that the weighting adjusted has reduced a reasonable degree of bias of the estimate. The percentage bias reduction of the volunteer panel web survey has been shown below.

Table 4.40. *Percentage of bias reduction of the estimate of the target variable by the post-stratification weighting for the volunteer panel web sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**57.00**	**-**
1. Gender	56.87	-7.22
2. Age	56.51	-27.22
3. Region	57.02	1.11
4. Working status	57.04	2.22
5. Marital status	57.02	1.11
6. Level of program in the study	**58.87**	**96.11**
7. Faculty in the study	57.05	2.78
Population	**58.80**	

Table 4.40 reveals the percentage bias reduction of the implemented seven weighting models in the volunteer panel web sample for the post-stratification weighting technique. The total bias reduction ratio out of all seven weighting models in the study—by the post-stratification weighting of the target variable (bias reduction >0%)—is 71.43%, and the total ratio of considerable bias reduction (bias reduction >50%) is 14.23%. The worst-case bias reduction ratio is 27.22%. The best bias reduction 96.11% has found in the post-stratification weighting model-6 (*Level of the program in the study*). Therefore, the estimates of the post-stratification weighting model-6 should be used for calculating the volunteer panel web sample estimates.

Table 4.41. *Percentage of bias reduction of the estimate of the target variable by the generalized regression modeling for the volunteer panel web sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**57.00**	**-**
1.Gender	57.42	23.33
2. Age	56.66	-18.89
3. Region	57.24	13.33
4. Working status	57.83	46.11
5. Marital status	57.61	33.89
6. Level of program in the study	56.54	-25.56
7. Faculty in the study	56.00	-55.56
8. Gender × Age	58.61	89.44
9. Gender × Region	57.53	29.44
10. Gender × Working status	**58.80**	**100**
11. Gender × Marital status	57.40	22.22
12. Age ×Working Status	**58.83**	**98.33**
13. Age × marital status	58.30	72.22
14. Gender × Age ×Working status	59.05	86.11
15. Gender + Age +Working status	57.40	22.22
16. Gender × Age × Region × Working status × Marital status × Level of program in the study × Faculty in the study	71.14	-585.56
17. Gender + Age + Region + Working status +Marital status + Level of program in the study +Faculty in the study	57.40	22.22
Population	**58.80**	

Percentage of bias reduction of the estimate of the target variable by generalized regression modeling for the volunteer panel web sample has been shown in Table 4.41. Dever, Rafferty, and Valliant (2008) observed that the bias reduction occurs in 23.9% estimates out of the total twenty-five estimates by the generalized regression modeling. The overall bias reduction ratio of the implemented seventeen weighting models in the study by the generalized regression modeling of the target variable (bias reduction >0%) is 76.47%, and the overall ratio of considerable bias reduction (bias reduction >50%) is 23.53%. The total worst bias reduction ratio is 28.57%. The bias has completely removed in the weighting model-10 (*Gender* × *Working status*). Thus, the estimates of the weighting model-10 should be used for computing the volunteer panel web sample estimates.

Table 4.42. *Percentage of bias reduction of the estimate of the target variable by the raking ratio estimation for the volunteer panel web sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**57.00**	**-**
1. Gender × Working status	**58.80**	**100**
2. Gender ×Working status ×Level of program in the study	58.24	69
3. Gender ×Working status ×Level of program in the study ×Region	58.33	74
4. Gender ×Working status ×Level of program in the study ×Region ×Age	58.61	90
5. Gender ×Working status ×Level of program in the study × Age	59.82	43
6. Gender ×Working status × Age	58.52	85
7. Gender ×Working status × Age ×Faculty in study	58.60	89
Population	**58.80**	**-**

Table 4.42 represents the percentage of bias reduction of the estimate of the target variable by the raking ratio estimation for the volunteer panel web sample. The raking ratio technique has observed that the reasonable (over 50%) bias reduction is occurred in 10.8% estimates out of total thirteen estimates (Berrens et al., 2003). The overall bias reduction ratio of implemented seven weighting models in the study by the raking ratio

estimation technique of the target variable (bias reduction >0%) is 100% and the total ratio of considerable bias reduction (bias reduction >50%) is 85.71%. The bias has 100% completely removed in the model-1 (*Gender × Working status*). Therefore, the estimate of the weighting model-1 should be used for computing the volunteer panel web sample estimates.

Table 4.43. *Percentage of bias reduction of the estimate of the target variable by the PSA for the volunteer panel web sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**57.00**	-
1.Gender	57.20	11
2.Working status	57.10	6
3.Gender×Working status	**57.98**	**55**
4. Gender ×Working status ×Level of program in the study	57.96	53
5. Gender ×Working status ×Level of program in the study ×Region	**57.98**	**55**
6. Gender ×Working status ×Level of program in the study ×Region ×Age	57.61	34
7. Gender ×Working status ×Level of program in the study × Age	**56.82**	**-46**
8. Gender ×Working status × Age	57.52	29
Population	**58.80**	**-**

Percentage of bias reduction of the estimate of the target variable by the PSA for the volunteer panel web sample has been illustrated in Table 4.43. The PSA approach observes that the proportion of over 50% bias reduction (reasonable) is found in 24.2% estimates out of the total twenty-four estimates (Schonlau, van Soest, and Kapteyn, 2007). The overall bias reduction ratio of eight weighting models which has been implemented in the study by the PSA of the target variable (bias reduction >0%) is 87.5%, and the total ratio of considerable bias reduction (bias reduction >50%) is 37.5%. The worst case has observed in model-7. The bias reduction 55% have occurred in both the model-3 and model-7. Therefore, the estimates of the weighting model-3 and model-5 should be used for computing the volunteer panel web sample estimates.

4.3.2. Percentage bias reduction for the random sample

In this section, the performance of the estimates of the implemented weighting models is determined by the percentage bias reduction for the random sample dataset. The percentage bias reduction of the random sample estimate of the target variable is displayed below.

Table 4.44. *Percentage of bias reduction of the estimate of the target variable by the post-stratification weighting for the random sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**58.90**	-
1. Gender	58.88	20.00
2. Age	58.97	-70.00
3. Region	**58.91**	**-100.00**
4. Working status	**58.81**	**90.00**
5. Marital status	58.89	10.00
6. Level of program in the study	58.83	70.00
7. Faculty in the study	58.91	-10.00
Population	**58.80**	**-**

Table 4.44 illustrates the percentage of bias reduction of the estimate of the target variable by the post-stratification weighting for the random sample. The total bias reduction ratio out of all seven weighting models by the post-stratification weighting of the target variable (bias reduction >0%) is 57.14%, and the total ratio of considerable bias reduction (bias reduction >50%) is 28.87%. The total worst-case bias reduction ratio is 42.87%. The best bias reduction 90% has found in the post-stratification weighting model-4 (*Working status*), and the worst bias reduction -100% has observed in the model-3 (*Region*). Therefore, the weighting model-4 should be considered for reducing the bias of the random sample estimate.

Table 4.45. *Percentage of bias reduction of the estimate of the target variable by the generalized regression modeling for the random sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**58.90**	**-**
1. Gender	59.00	-100
2. Age	58.20	-500
3. Region	59.00	-100
4. Working status	59.00	-100
5. Marital status	58.10	-600
6. Level of program in the study	59.00	-100
7. Faculty in the study	59.00	-100
8. Gender × Age	58.90	0
9. Gender ×Region	59.00	-100
10. Gender × Working status	**58.80**	**100**
11. Gender × Marital status	58.00	-700
12. Age ×Working Status	58.00	-700
13. Age × marital status	58.30	-400
14. Gender × Age ×Working status	59.00	-100
15. Gender + Age +Working status	59.00	-100
16. Gender × Age × Region × Working status × Marital status × Level of program in the study × Faculty in the study	**57.00**	**-1700**
17. Gender + Age + Region + Working status +Marital status + Level of program in the study +Faculty in the study	59.00	-100
Population	**58.80**	**-**

Percentage of bias reduction of the estimate of the target variable by the generalized regression modeling for the random sample has been demonstrated in Table 4.45. The total bias reduction ratio of seventeen weighting models which has been implemented in the study—by the generalized regression estimation of the target variable (bias reduction >0%)—is 5.88%, and the total ratio of considerable bias reduction (bias reduction >50%) is 5.88%. The overall worst bias reduction ratio is 88.23%. The bias has wholly removed in the model-10 (*Gender × Working status*). All the implemented weighting models has got worse after adjusted the weight except the weighting model-10. The model-10 has reduced the bias by 100%. Therefore, model-10 should be used for calculating the random sample estimates.

Table 4.46. *Percentage of bias reduction of the estimate of the target variable by the raking ratio estimation for the random sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**58.90**	
1. Gender × Working status	**58.75**	**50**
2. Gender ×Working status ×Level of program in the study	58.00	-700
3. Gender ×Working status ×Level of program in the study ×Region	58.20	-500
4. Gender ×Working status ×Level of program in the study ×Region ×Age	58.20	-500
5. Gender ×Working status ×Level of program in the study× Age	60.00	-100
6. Gender ×Working status × Age	58.00	-700
7. Gender ×Working status × Age × Faculty in the study	58.00	-700
Population	**58.80**	**-**

Table 4.46 represents the percentage of bias reduction of the estimate of the target variable by the raking ratio estimation for the random sample. Yeager et al., (2011) observed that bias reduction is found in 42% estimates of sample 1 out of the total nineteen estimates by the raking ratio technique. Here, only the weighting model-1 *(Gender × Working status)* has removed the bias by 50%. The remaining six weighting models have a negative percentage of bias reduction. This indicates that bias has got worse after raking ratio adjusted.

Table 4.47. *Percentage of bias reduction of the estimate of the target variable by the PSA for the random sample*

Weighting model	Estimate (%)	Bias reduction (%)
No weighting	**58.90**	-
1. Gender	58.72	20
2. Working status	58.70	0
3. Gender × Working status	58.77	70
4. Gender ×Working status ×Level of program in the study	58.96	-60
5. Gender ×Working status ×Level of program in the study ×Region	58.98	-80
6. Gender ×Working status ×Level of program in the study ×Region ×Age	59.00	-100
7. Gender ×Working status ×Level of program in the study × Age	**58.82**	**80**
8. Gender ×Working status × Age	**58.52**	**-500**
Population	**58.80**	**-**

Table 4.47 shows the percentage bias reduction of the random sample for the PSA technique. The total bias reduction ratio out of all eight weighting models by the PSA of the target variable (bias reduction >0%) is 37.50%, and the total ratio of considerable bias reduction (bias reduction >50%) is 25%. However, the worst case has observed in model-8, and its bias reduction is -500%. The 80% bias reduction has found in the weighting model-7. Therefore, model-7 should be considered for computing the random sample estimates.

4.4. Comparison Between Volunteer Panel Web Sample and Random Sample Estimates

Observed Adjustment have been performed by the χ^2 test because of categorical covariates in each weighting model which has been implemented in the study to decide whether differences between before and after adjustment bias reduction is significant. The tests have been performed for both the volunteer panel web sample and population data. The volunteer panel web sample estimate and the population estimate are significantly different after weighting adjustment.

To illustrate the performance of the weighting estimates based on different weighting models, the volunteer panel web sample estimate and its standard errors have been compared to the random sample estimates by the implemented four weighting adjustment techniques in the study. Empirical relative bias is computed to distinguish between the volunteer panel web sample and random sample estimates.

According to Bethlehem and Biffignandi (2012), if T is an estimator, θ is the parameter of interest, and *MSE (T)* is the empirical mean square error of the estimator T, then relative bias (*RB*) is defined by:

$$RB = \frac{T-\theta}{\sqrt{MSE(T)}} \tag{4.2}$$

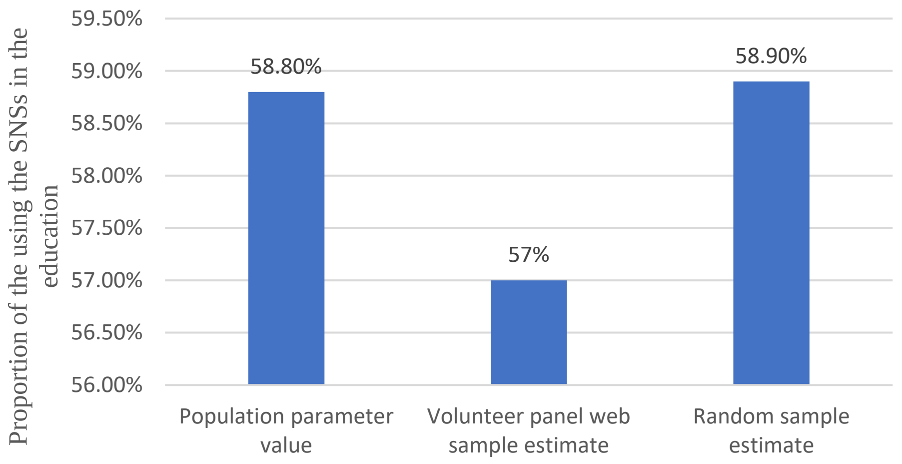

Figure 4.5. *Comparison of the volunteer panel web sample estimate and random sample estimate with the population parameter value*

Figure 4.5 depicts the comparison of the volunteer panel web sample and random sample estimates with population estimates. The proportion of the using the SNSs in the education is 58.80% whereas the volunteer panel web sample estimate is 57%, and random sample estimate is 58.90%. The random sample estimate is almost equal to the population parameter value. Thus, the random sample estimate is more precise than the volunteer panel web sample estimate.

4.4.1. Comparison between volunteer panel web sample and random sample estimates by the post-stratification weighting

In this section, the study describes the comparison between volunteer panel web sample and random sample estimates by considering four techniques.

Table 4.48 represents the comparison between the volunteer panel web sample (non-probability) and random sample estimates with respect to the relative bias of the estimates. The relative biases of the random sample estimates are lower than the volunteer panel web sample estimates for all the implemented post-stratification weighting models in the study. Therefore, random sample estimates are better for post-stratification weighting models compared to the volunteer panel web sample estimates (non-probability-based web sample).

Table 4.48. *Comparison between the volunteer panel web sample and random sample estimates of the target variable for the post-stratification weighting technique*

	Volunteer panel web survey (non-probability)			**Random sample**		
Weighting model	**Estimate (%)**	**Standard error**	**Relative bias**	**Estimate (%)**	**Standard error**	**Relative bias**
No weighting	**57.00**	**0.9160**	**-1.9651**	**58.90**	**1.0000**	**0.1000**
1. Gender	56.87	0.9667	-1.9965	58.88	1.0094	0.0793
2. Age	56.51	1.2217	-1.8744	58.97	0.9475	0.1794
3. Region	57.02	0.9156	-1.9443	58.91	1.0069	0.1092
4.Working status	57.04	0.9155	-1.9224	58.81	0.9500	0.0105
5. Marital status	57.02	0.8961	-1.9864	58.89	0.6948	0.1295
6. Level of program in the study	58.87	0.9025	0.0776	58.83	1.0045	0.0299
7. Faculty in the study	57.05	0.9244	-1.8931	58.91	1.2745	0.0863
Population	**58.80**		**-**	**58.80**		**-**

4.4.2. Comparison between the volunteer panel web sample and random sample estimates for the generalized regression modeling

Comparison between the volunteer panel web sample and random sample estimates for the generalized regression modeling has been represented in Table 4.49. Here, in the generalized regression modeling, the random sample estimates are better than the volunteer panel web sample estimates. In contrary, the relative bias of the random sample estimates is smaller than the volunteer panel web sample estimates. The relative bias of the model-10 is zero both in the volunteer panel web sample and random sample estimates. Therefore, the estimate of the weighting model-10 is unbiased both in the volunteer panel web sample and random sample estimates.

Table 4.49. *Comparison between the volunteer panel web sample and random sample estimates of the target variable for the generalized regression modeling technique*

	Volunteer panel web survey (non-probability)			**Random sample**		
Weighting model	**Estimate (%)**	**Standard error (%)**	**Relative bias**	**Estimate (%)**	**Standard error (%)**	**Relative bias**
No weighting	**57.00**	**0.915**	**-1.9672**	**58.90**	**1.00**	**0.1000**
1. Gender	57.42	1.205	-1.1452	59.00	1.30	0.1538
2. Age	56.66	0.584	-3.6643	58.20	0.50	-1.2000
3.Region	57.24	0.775	-2.0129	59.00	0.70	0.2857
4. Working status	57.83	0.819	-1.1843	59.00	0.70	0.2857
5. Marital status	57.61	1.310	-0.9083	58.10	0.80	-0.8750
6. Level of program in the study	56.54	1.238	-1.7447	59.00	1.40	0.1428
7. Faculty in the study	56.00	1.912	-1.4644	59.00	0.80	0.2500
8. Gender × Age	58.61	0.753	-0.2523	58.90	0.70	0.1428
9. Gender × Region	57.53	1.029	-1.2342	59.00	0.80	0.2500
10. Gender × Working status	**58.80**	**0.998**	**0**	**58.80**	**0.90**	**0**
11. Gender × Marital status	57.40	1.759	-0.7959	58.00	1.10	-0.7272
12. Age ×Working Status	58.83	0.505	0.0055	58.00	0.30	-2.6667
13. Age × marital status	58.30	0.745	-0.6711	58.30	0.40	-1.2500

Table 4.49. (Continued) *Comparison between the volunteer panel web sample and random sample estimates of the target variable for the generalized regression modeling technique*

	Volunteer panel web survey (non-probability)			Random sample		
Weighting model	**Estimate (%)**	**Standard error (%)**	**Relative bias**	**Estimate (%)**	**Standard error (%)**	**Relative bias**
14. Gender × Age ×Working status	59.05	0.610	0.4098	59.00	0.40	0.5000
15. Gender + Age +Working status	57.40	0.442	-3.1674	59.00	0.40	0.5000
16. Gender × Age × Region × Working status × Marital status × Level of program in the study × Faculty of study	71.14	1.522	8.1077	57.00	0.20	9
17. Gender + Age + Region + Working status +Marital status + Level of program in the study +Faculty in the study	57.40	0.347	-4.0345	59.00	0.30	0.6667
Population	**58.80**	**-**	**-**	**58.80**	**-**	**-**

4.4.3. Comparison between the volunteer panel web sample and random sample estimates by raking ratio estimation technique

Table 4.50 shows the comparison between the volunteer panel web sample and random sample estimates of the target variable for the raking ration estimation technique. It has observed that the relative bias of the random sample estimates is small compared to the volunteer panel web sample estimates except the weighting model-4 and model-7. The relative bias of the weighting model-7 is zero in the random sample data which means that the estimate of the weighting model-7 is unbiased. Therefore, random sample estimates are better than the volunteer panel web sample estimates.

Table 4.50. *Comparison between the volunteer panel web sample and random sample estimates of the target variable for the raking ration estimation technique*

	Volunteer panel web survey (non-probability)			Random sample		
Weighting model	**Estimate (%)**	**Standard error (%)**	**Relative bias**	**Estimate (%)**	**Standard error (%)**	**Relative bias**
No weighting	**57.00**	**0.915**	**-1.9672**	**58.90**	**1.00**	**0.1000**
1. Gender ×Working status	58.58	0.913	-0.2409	58.75	1.60	-0.0313
2. Gender ×Working status ×Level of program in the study	58.24	0.913	-0.6134	58.00	1.60	-0.500
3. Gender ×Working status ×Level of program in the study ×Region	58.33	0.913	-0.5153	58.20	2.70	-0.2222
4. Gender ×Working status ×Level of program in the study ×Region ×Age	58.61	0.912	-0.2083	58.20	2.70	-0.2222
5. Gender ×Working status ×Level of program in the study × Age	59.82	0.907	0.0221	60.00	1.10	1.0909
6. Gender ×Working status × Age	58.52	0.912	-0.3070	58.00	1.00	0
7. Gender ×Working status × Age ×Faculty in the study	58.60	0.926	-0.2160	58.00	1.30	-0.6153
Population	**58.80**	**-**	**-**	**58.80**	**-**	**-**

4.4.4. Comparison between the volunteer panel web survey sample and random sample estimates by the PSA technique

Table 4.51 illustrates the comparison between the volunteer panel web sample and random sample estimates of the target variable for the PSA technique. It has revealed that the random sample estimates are better than the volunteer panel web sample estimates. The relative biases in the PSA weighting models of random sample are smaller than the volunteer panel web sample relative biases. Thus, the random sample estimates are more accurate than the volunteer panel web sample estimates.

Table 4.51. *Comparison between the volunteer panel web sample and random sample estimates of the target variable for the PSA technique*

	Volunteer panel web survey (non-probability)			**Random sample**		
Weighting model	**Estimate (%)**	**Standard error (%)**	**Relative bias**	**Estimate (%)**	**Standard error (%)**	**Relative bias**
No weighting	**57.00**	**0.915**	**-1.9672**	**58.90**	**1.00**	**0.1000**
1. Gender	57.20	0.912	-1.7543	58.72	0.812	-0.9852
2. Working status	57.10	0.911	-1.8661	58.70	0.811	-0.1233
3. Gender × Working status	57.98	0.692	-1.1849	58.77	0.692	-0.0433
4. Gender ×Working status ×Level of program in the study	57.96	0.613	-1.3703	58.96	0.713	0.2244
5. Gender ×Working status ×Level of program in the study ×Region	57.98	0.613	-1.3377	58.98	0.713	0.2524
6. Gender ×Working status ×Level of program in the study ×Region ×Age	57.61	0.612	-1.9444	59.00	0.912	0.2192
7. Gender ×Working status ×Level of program in the study × Age	56.82	0.907	-2.1830	58.82	0.807	0.0247
8. Gender ×Working status × Age	57.52	0.912	-1.4035	58.52	0.912	-0.3070
Population	**58.80**	**-**	**-**	**58.80**	**-**	

5. DISCUSSION AND CONCLUSION

This study explores the relative merits of different weighting models of selected auxiliary variables, post-stratification weighting adjustment, generalized regression modeling, raking ratio estimation and propensity score adjustment techniques for reducing bias in the volunteer panel web survey. In section 5.1, it elucidates the evaluation of the results of this study and some discussion, whereas, the section 5.2 concludes this study.

5.1. Discussion

The prime objective of the study is to reveal the characteristics and problems (coverage, self-selection, and non-response errors) of web surveys as well as resolve the problems and ascertain the more precise estimates. To do so, it implements four weighting adjustment techniques—post-stratification weighting, generalize regression weighting, raking ratio estimation, and propensity score adjustment—to reduce the bias of the under-coverage or self-selection or non-response errors and conducts a volunteer panel web survey. The primary objective of the survey is to compute an unbiased estimator with minimal variance. Alongside, it also endeavors to explore the weighting adjustment technique which one provides more precise estimate. Here, in this survey, on the one hand, it considers a sample size of 2920. On the other hand, a simulated random sample of size 2396 has been created by means of probability sampling design (stratified). Finally, the volunteer panel web sample estimates are compared to the random sample estimates. Here, the parameter value of the population, the volunteer panel web survey estimate, and random sample estimate are 58.80%, 57.00%, and 58.90% respectively. Thus, the volunteer panel web sample estimate is a biased estimate and downward biased, however, the simulated random sample estimate is upward biased, and almost equal to the parameter value. Therefore, the random sample estimate is better than the volunteer panel web sample estimate.

Now, taking consideration into the application of the techniques, firstly, the post-stratification weighting adjustment technique is applied to reduce the bias in the volunteer panel web survey. To ensure conspicuous findings, seven weighting models have been considered for the post-stratification weighting technique both in the volunteer panel web and random sample data. These models provide some very significant estimates. Here, the results evince that the bias has absolutely removed from the volunteer panel web survey when selected auxiliary variables are used as a post-stratification weight, but the bias of the target variable estimate did not completely remove because there has no strong relationship between the selected auxiliary variables and the target variable. In the volunteer panel web survey, the bias has reduced by 96.11% as the variable, *Level of the program in the study*, (model-6) which is used as a post-stratification weight, whereas, in the random sample, the bias has reduced by 90% as the variable the ,*Working status*, (model-4) which is utilized as a post-stratification weight, and these reductions of bias has lessened standard error also. However, some negative bias reductions have observed in the post-stratification weighting models.

Secondly, in the volunteer panel web survey, seventeen weighting models have been implemented in the generalized regression modeling technique. The total bias reduction ratio out of all the seventeen weighting models by the generalized regression modeling of the target variable (bias reduction >0%) is 76.47%, and the considerable bias reduction ratio (bias reduction >50%) is 23.53%. In this technique, the weighting model-10 has been created by crossing the variables, *Age* and *Working status*. The estimate of the weighting model-10 reduces the bias by 98.33% and standard error too. On the other hand, the total bias reduction ratio of the random sample estimate of the target variable (bias reduction >0%) is 5.88%, and the considerable bias reduction ratio (bias reduction >50%) is 5.88%. The bias has completely removed from the model-10 that is the same weighting model in the volunteer panel web survey. Therefore, both the volunteer panel web survey sample and random sample data have the same weighting model-10 which has completely reduced the bias.

Thirdly, the raking ratio technique has been used seven weighting models both in the volunteer panel web sample and random sample data. The total bias reduction ratio of the volunteer panel web sample estimates out of all the implemented seven weighting models of the target variable (bias reduction >0%) is 100% which means that every weighting model has reduced the bias. Alongside, the considerable bias reduction ratio (bias reduction >50%) is 85.71%. The weighting model-1 has been created by crossing the auxiliary variables, *Gender* and *Working status,* which obtained the unbiased estimate to the parameter. On the other side, in the random sample, the total bias reduction ratio of the raking ratio estimate (bias reduction >0%) is 14.29%, and the overall ratio of considerable bias reduction (bias reduction >50%) is 14.29%. Noticeably, only the weighting model-1 has removed the bias by 50%. The bias of the remaining six weighting models has become worse after implementing the raking ratio estimation. Therefore, raking ratio technique has not performed efficiently for the random sample data.

Finally, sub-classification propensity score adjustment and calibration adjustment techniques has observed that the bias reduction occurred in 67% variables out of total twelve variables, and the proportion of over 50% bias reduction rate is 42% variables (Lee, 2011). Huh and Cho (2009) showed that the PSA and raking ratio estimation techniques reduce bias by 35%. In the case of the volunteer panel web survey, PSA technique has shown that the bias reduction occurs in 87.50% weighting models out of the implemented eight weighting models. The ratio of the considerable bias reduction has 37.50% weighting models. This percentage seems to be reasonable compared to Huh and Cho (2009) and Lee (2011). On the contrary, in the random sample has been considered the eight weighting models where PSA has reduced the bias in 37.50% weighting models and the proportion of over 50% (considerable) bias reduction of 25% weighting models and the variance of the estimate has reduced as well. This fact indicates that the PSA has not performed well for the random sample data compared to the volunteer panel web sample data.

Here, PSA technique may not work for large surveys because it is tough to meet ‘strong ignore-ability assumption' for all responses. However, matching method may be another solution to the improvement of bias reduction (Lee, 2011). The matching method can be worked well where there are a restricted number of treated group individuals and many control group members. Another cause for the weak bias reduction in PSA technique may be a violation of some assumptions during the analysis.

In this section, the study elucidates the comparative analysis of two samples—volunteer panel web and random—by considering four weighting adjustment techniques. In the volunteer panel web sample, the post-stratification weighting technique has reduced the bias of the estimate by 96.11% of the weighting model-6 (*Level of the program in the study)* that is the most significant bias reduction combination of the implemented weighting models. On the other hand, in the random sample, the weighting model-4 (*Working status)* has obtained in 90% bias reduction which is the best bias reduction model.

The weighting model-10 has been created by crossing the variable, *Gender* and *Working status*, in both the volunteer panel web sample and random sample data has reduced the bias by 100% of the target variable that is the unbiased estimate of the parameter for both the generalized regression modeling and raking ratio estimation techniques.

Now, considering the PSA technique, in the volunteer panel web sample, the weighting model-3 and model-5 have reduced bias by 55%, whereas, in the random sample, the weighting model-7 has reduced bias by 80%. These bias reductions of both samples denote that PSA technique is more effective for random sample compared to the volunteer panel web sample.

Finally, to ascertain perspicuous and accurate findings, a relative bias of the estimate always provides more precise estimates. The relative bias of the estimates is computed for comparison between the volunteer panel web sample and random sample datasets. The implemented four weighting adjustment techniques have found that the relative biases of the random sample estimates for all the weighting models is smaller than the volunteer panel web sample estimates. It concludes that the random sample estimates are better than the volunteer panel web sample estimates.

In summary, taking consideration of all the findings, it can be mentioned that if weighting adjustment techniques are implemented in the volunteer panel web survey estimate, the adjusted estimates will provide better results than random sample estimates.

5.2. Conclusion

Recently, web surveys have become familiar because of their attractive features in data collection. However, non-probability-based web surveys cause problems—coverage, self-selection and non-response. Numerous researches have been performed on web surveys, specifically, volunteer web panel surveys, to address the above issues and provide solutions. Until now, researchers have utilized post-stratification weighting, generalized regression modeling, calibration adjustment and propensity score adjustment for web surveys. The post-stratification weighting method has been used for reducing the bias of the target variable. Bias has been reduced substantially, but not completely removed because the target variable is not correctly associated with the selected auxiliary variables. For the generalized regression modelling technique, weighting models have been created by crossing or adding auxiliary variables. These adjustments have provided better results than post-stratification adjustment technique. This technique performs well when there is a linear relationship between target variable(s) and auxiliary variables. For the calibration adjustment technique, raking ratio weight has been explored. Usually, this technique is used when there is a log-linear relationship between the target variable(s) and the auxiliary variables. It gives better results than post-stratification and generalized regression modelling adjustment techniques. Now, for propensity score adjustment, the inverse propensity scores weighting method has been considered. Inverse propensity score weighting has yielded superior results than propensity score adjustment. The weighting adjustment techniques cannot be performed well because of the violation of assumption of the adjustment techniques. Specifically, propensity score adjustment technique may not be performed for the big survey because sometimes "strong ignore-ability assumption" is violated.

The study has compared the estimates of a simulated random sample having internet access to those from a non-probability-based volunteer panel web survey. The conclusion is that the random sample estimates are better than those from the volunteer panel web survey.

Nevertheless, web survey research should continue because of its huge benefits and extensive technological development in the current world. If any researcher would like to conduct a research considering web survey, volunteer panel web surveys would be the best option for the researcher. The study also recommends that in scientific research or commercial market research, volunteer panel web surveys would provide the high-quality data with minimum time and cost. Most importantly, if any bias occurs, it can be removed by applying at least one of the weighting adjustment techniques implemented in this study.

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APPENDIX-1

Questionnaire:

"Using Social Networking Sites in the Education of Students of Open Education System, Anadolu University".

This questionnaire is prepared to reveal the profile of Anadolu University Open Education System students' use of social networking sites in the education. The data of this questionnaire prepared for use in the doctoral dissertation will not be used for any other purpose. Thank you for participating in the survey.

Q1. Gender

- Male
- Female

Q2. Please, select your age.

- <20 years
- 20-25 years
- 25-30 years
- 30-35 years
- 35-40 years
- 40-45 years
- >45 years

Q3. Region

- Metropolitan
- Urban
- Rural

Q4. What is your occupation?

- Full-time working
- Part-time working
- Not-working

Q5. Please, select your marital status.

- Single
- Married
- Divorced
- Widowed

Q6. What is your faculty in studying?

- Open Education Faculty
- Faculty of Economics
- Faculty of Business Administration

Q7. What is the level of program in studying?

- Two-year associate degree program
- Four-year Bachelor’s degree program
- Certificate program

Q8. What is your profession?

Q9. Do you use social networking sites in the education which are today's indispensable tools in Open Education System? (If answer is no, go to question 23).

- Yes
- No

Q10. Why do you use social networking sites in the education in Open Education System? (You can select more than one)

- Inspirational teaching methods and learning styles.
- Diversity in education
- Reciprocal teaching
- Promote interacting learning
- The growth mindset

Q11. Which, if any social networking sites in the education do you use? (You can select more than one)

- Myspace
- Facebook
- Bebo
- Flixster
- His
- LinkedIn
- Orkut
- Twitter
- Google+
- Other, please specify:

Q12. Which, if any social bookmarking sites in the education do you use? (You can select more than one)

- Delicious
- StumbleUpon
- Memosing
- Myspace
- CyberHome
- Google Bookmarks
- Other, please specify:

Q13. Which, if any social calendaring sites in your education do you use? (You can select more than one)

- Google
- Outlook
- iCal
- Yahoo
- Doole
- My mobile
- Other, please specify:

Q14. Which, if any social image (photo) sharing sites in your education do you use? (You can select more than one)

- Flicker
- Slide
- Zofo
- Instagram
- Photo Bucket
- Picasa
- Ringo
- Other, please specify:

Q15. Which, if any collaborative authoring sites in the education do you use? (You can select more than one)

- Wikispace
- Wikipedia
- Writely

- Rallypoint
- Academia.edu
- Other, please specify:

Q16. Which, if any video sharing sites in the education do you use? (You can select more than one)

- YouTube
- Daily Motion
- Facebook
- Google Videos
- Other, please specify:

Q17. Which, if any blogging sites in the education do you use? (You can select more than one)

- Your own blog
- Other people blogs
- Blogs run by institutions
- Bloglines
- Other, please specify:

Q18. Which, if any file sharing sites in the education do you use? (You can select more than one)

- Napster
- Kazaa
- Grokster
- Rapidshare
- Google Drive
- Dropbox
- Mediafire
- OneDrive
- OneDrive
- Other, please specify:

Q19. Which, if any communication tools sites in the education do you use? (You can select more than one)

- Skype
- iChat

- MSN Messenger
- Yahoo Messenger
- Google Talk
- Discussion forums
- Facebook chat
- WhatsApp
- Viber
- imo
- Other, please specify:

Q20. What are the ICT tools that you have? (You can select more than one)

- Smart Phone
- PC
- Tablet PC/iPad
- Only PC
- Only Smart Phone
- All tools

Q21. How often, if at all, in the education do you use social networking sites?

- Daily
- Weekly
- Monthly
- Occasionally
- No longer use
- Never used
- Thinking of using
- Never heard of it

Q22. How do you use social networking systems in the education?

- View/Read
- Write/Contribute
- Moderate control

Q23. Do you think social networking sites are important in the education?

- Strongly agree
- Agree

- Neither agree nor disagree
- Disagree
- Strongly disagree

Q24. Do you think social networking sites are efficient for learning in the education?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q25. Do you think social networking sites are efficient for e-library?

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q26. What is your suggestions about the "Using Social Networking Sites in the Education of Students of Open Education System, Anadolu University"?

APPENDIX-2

AÇIK ÖĞRETİM SİSTEMİNDE ÖĞRENCİLERİN EĞİTİMDE SOSYAL AĞ KULLANIMI

ARAŞTIRMA GÖNÜLLÜ KATILIM FORMU

Bu çalışma, İnternet Anketlerinin İstatistiksel Analizi başlıklı bir araştırma çalışması olup Doktora tez çalışması olup internet anketlerinde istatistiksel tekniklerin nasıl kullanılacağını ortaya koymak amacını taşımaktadır. Çalışma, Md Musa Khan tarafından yürütülmekte ve sonuçları ile İstatistiksel olarak internet anketlerinin tasarlanmasıı ortaya konacaktır / internet anketlerinin tasarlanması, uygulanması ve bunlardan sonuç çıkartılmasına yönelik istatistiksel hataların giderilmesine yönelik gelişimine ışık tutulacaktır.

• Bu çalışmaya katılımınız gönüllülük esasına dayanmaktadır.
• Çalışmanın amacı doğrultusunda, anket yapılarak sizden veriler toplanacaktır.
• İsminizi yazmak ya da kimliğinizi açığa çıkaracak bir bilgi vermek zorunda değilsiniz/araştırmada katılımcıların isimleri gizli tutulacaktır.
• Araştırma kapsamında toplanan veriler, sadece bilimsel amaçlar doğrultusunda kullanılacak, araştırmanın amacı dışında ya da bir başka araştırmada kullanılmayacak ve gerekmesi halinde, sizin (yazılı) izniniz olmadan başkalarıyla paylaşılmayacaktır.
• İstemeniz halinde sizden toplanan verileri inceleme hakkınız bulunmaktadır.
• Sizden toplanan veriler bilgisayarda istatistiksel programlarda dosyalama yöntemi ile korunacak ve araştırma bitiminde arşivlenecek veya imha edilecektir.
• Veri toplama sürecinde/süreçlerinde size rahatsızlık verebilecek herhangi bir soru/talep olmayacaktır. Yine de katılımınız sırasında herhangi bir sebepten rahatsızlık hissederseniz çalışmadan istediğiniz zamanda ayrılabileceksiniz. Çalışmadan ayrılmanız durumunda sizden toplanan veriler çalışmadan çıkarılacak ve imha edilecektir.

Gönüllü katılım formunu okumak ve değerlendirmek üzere ayırdığınız zaman için teşekkür ederim. Çalışma hakkındaki sorularınızı Anadolu Üniversitesi İstatistik bölümünden Zerrin Aşan Greenacre 'ye (zasan@anadolu.edu.tr/09022223350581/4663) yöneltebilirsiniz.

Araştırmacı Adı :Md Musa KHAN
Adres :Yunusemre Öğrenci Yurdu

1

AÇIK ÖĞRETİM SİSTEMİNDE ÖĞRENCİLERİN EĞİTİMDE SOSYAL AĞ KULLANIMI

Bu çalışmaya katılımınız gönüllülük esasına dayanmaktadır

Bu anket Anadolu Üniversitesi Açık Öğretim Sisteminde öğrencilerin eğitimde sosyal ağ sitelerinin kullanımına ilişkin profilini ortaya çıkarmak üzere hazırlanmıştır. Doktora tezinde kullanılmak üzere hazırlanan bu anketin verileri başka bir amaçla kullanılmayacaktır. Ankete katıldığınız için teşekkür ederiz.

* 1. **Cinsiyetiniz**

- Erkek
- Kadın

* 2. **Yaşınız**

- <20 yaş
- 20-25 yaş
- 25-30 yaş
- 30-35 yaş
- 35-40 yaş
- 40-45 yaş
- >45 yaş

* 3. **Bölgeniz**

- Metropoliten (Büyük Şehir)
- Şehir
- Köy

* 4. **Çalışma durumunuz**

- Tam zamanlı çalışıyor
- Yarı zamanlı çalışıyor
- Çalışmıyor

2

* 5. **Aile durumunuz**

- ◯ Bekar
- ◯ Evli
- ◯ Boşanmış
- ◯ Dul

* 6.

Hangi fakültede okuyorsunuz?

- ◯ Açik Öğretim fakültesi
- ◯ İktisat fakültesi
- ◯ İşletme fakültesi

* 7.

Program seviyeniz nedir?

- ◯ 2- senelik lisans programı
- ◯ 4 -senelik lisans programı
- ◯ Sertifika programı

* 8. **Mesleğiniz nedir?**

* 9.

Açık Öğretim Sisteminde günümüzün vazgeçilmez araçları olan sosyal paylaşım sitelerini kullanıyor musunuz?

- ◯ Evet
- ◯ Hayır (23. Soruya geçiniz.)

3

*** 10.**

Neden açık öğretim sisteminde sosyal paylaşım sitelerini kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ İlham veren öğretim yöntemleri ve öğrenme stilleri
- ◯ Eğitimde çeşitlilik
- ◯ Karşılıklı öğretim
- ◯ Etkileşimli öğrenmeyi teşvik edin
- ◯ Büyüme zihniyet

*** 11.**

Hangi sosyal ağ sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Myspace
- ◯ Facebook
- ◯ Bebo
- ◯ Flıxoter
- ◯ Hıs
- ◯ LinkedIn
- ◯ Orcid
- ◯ Twitter
- ◯ Goole+
- ◯ Diğer, lütfen belirleyiniz:

*** 12.**

Hangi sosyal imleme (bookmarking) sitelerini kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Delicious
- ◯ Stumble upon
- ◯ Memosing
- ◯ MySpace
- ◯ Cyberhome
- ◯ Google Bookmarks
- ◯ Diğer, lütfen belirleyiniz:

* 13.

Hangi sosyal takvim sitelerini kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Google
- ◯ Outlook
- ◯ iCal
- ◯ Yahoo
- ◯ Doodle
- ◯ Mymobile
- ◯ Diğer, lütfen belirleyiniz:

* 14.

Hangi görüntü (Photo) paylaşım sitelerini kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Flickr
- ◯ Slide
- ◯ Zofo
- ◯ Instagram
- ◯ PhotoBucket
- ◯ Pıcasa
- ◯ Ringo
- ◯ Diğer, lütfen belirleyiniz:

* 15.

Hangi işbirlikçi otorite (collaborative authoring) sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Wikispaces
- ◯ Wikipedia
- ◯ Writely
- ◯ Rallypoint
- ◯ Academia.edu
- ◯ Diğer, lütfen belirleyiniz:

5

* 16.

Hangi video paylaşım sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Youtube
- ◯ Daylimotion
- ◯ Facebook
- ◯ Google Videos
- ◯ Diğer, lütfen belirleyiniz:

* 17.

Hangi blog sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Kendi blog
- ◯ Diğer insanların bloğu
- ◯ Enstitu/şirket blogları
- ◯ Bloglines
- ◯ Diğer, lütfen belirleyiniz:

* 18.

Hangi dosya paylaşım sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- ◯ Napster
- ◯ Kaza
- ◯ Grokster
- ◯ Rapidshare
- ◯ Google Drive
- ◯ Dropbox
- ◯ Mediafire
- ◯ OneDrive
- ◯ Diğer, lütfen belirleyiniz:

6

* 19.

Hangi iletişim araçlar sitelerini eğitimde kullanıyorsunuz? (Birden fazla yanıt seçebilirsiniz.)

- Skype
- iChat
- MSN Messenger
- Yahoo Massenger
- Google Talk
- Discussion forums/Tartışma forumları
- Facebook sohbeti
- Whatsapp
- Viber
- İmo
- Diğer, lütfen belirleyiniz:

* 20.

Hangi BİT (ICT) araçlarını kullanıyorsunuz?

- Akıllı telefon
- Bilgisayar
- Tablet PC/iPad
- Sadece Bilgisayar
- Sadece Akıllı telefon
- Hepsi

* 21.

Ne sıklıkta sosyal ağ sistemlerini kullanıyorsunuz?

- Her gün
- Haftalık
- Aylık
- Bazen/ bir aydan daha az
- Artık kullanmıyorum
- Hiç kullanmadım
- Kullanmayı düşünmüyorum
- Hiç gerekli değildi

* 22.

Sosyal ağ sistemlerini eğitimde nasıl kullanıyorsunuz?

- ◯ İnceliyorum/Okuyorum
- ◯ Katkıda bulunuyorum/Yazıyorum
- ◯ Kontrol ediyorum

* 23.

Sosyal ağ sitelerinin eğitimde önemli olduğunu düşünüyor musunuz?

- ◯ Kesinlikle katılıyorum
- ◯ Katılıyorum
- ◯ Ne katılıyorum ne de katılmıyorum
- ◯ Katılmıyorum
- ◯ Kesinlikle katılmıyorum

* 24.

Sosyal ağ sitelerinin eğitimde öğrenme için etkili olduğunu düşünüyor musunuz?

- ◯ Kesinlikle katılıyorum
- ◯ Katılıyorum
- ◯ Ne katılıyorum ne de katılmıyorum
- ◯ Katılmıyorum
- ◯ Kesinlikle katılmıyorum

* 25.

Sosyal ağ sitelerinin e-kütüphaneyi kullanmak için verimli olduğunu düşünüyor musunuz?

- ◯ Kesinlikle katılıyorum
- ◯ Katılıyorum
- ◯ Ne katılıyorum ne de katılmıyorum
- ◯ Katılmıyorum
- ◯ Kesinlikle katılmıyorum

8

* 26.

Anadolu Üniversitesi Açık Öğretim Sisteminde Öğrencilerin Sosyal Ağ Sitelerinin Kullanımı ile ilgili önerileriniz nelerdir? Lütfen belirleyiniz:

Ankete katıldığınız için teşekkür ederiz.