Combining Information from Web Based Survey and Telephone Survey

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An on-line survey on the Internet, a web survey, is a new way of collecting data from the users of a web site. However, if answering is voluntary, a low response rate can be expected, and an analysis based on the observed data alone may give biased and misleading results due to self selection. The research question we address in this paper is; what solutions can be recommended to correct for the possible bias due to non-response? Our suggestion is to perform an additional survey, with better quality with respect to the response rate and self selection bias, to combine the two surveys by statistical modelling. This approach is used to study a specific web site, where data were collected both by web and telephone surveys.

1 Introduction

In marketing research there are a number of data-collection tools available. One of the most popular is telephone interviewing (CATI). The Internet revolution has given opportunities for other ways of collecting survey data. For instance, E-mail based surveys have been used for a while. These are surveys where either a questionnaire is sent by email in text-format, or an invitation to participate in a survey is sent by email. With the growth of the WWW on the Internet in the last 3 - 4 years, the question of how to collect data through the web has been raised. An example is Peterson, Balasubramanian and Bronnenberg (1997) who write "A second aspect of the Internet that has attracted attention is its potential in the marketing research arena". However, these authors do not refer to any empirical studies.

In contrast to well-known methods such as postal and telephone surveys, Internet data-collection methods have not been much tested or studied so far (Smith 1997; Frost 1998). However, it seems they are getting more and more attention. For instance, in January 1998 the European Society of Opinion and Marketing Research held a seminar on Internet and market research. At this seminar one of the speakers ended his presentation by saying "It is only a matter of time before on-line surveys will be commonplace. The market research industry has very little choice in this. Either we find a way to conduct statistically reliable and predictable results from on-line surveys or our clients will move to on-line research without us." (Gates and Helton 1998).

In this paper, we consider web-based surveys. A web-based survey is here defined as an html-questionnaire, a questionnaire on the web which pops up on a particular web site. This definition does not include links to a questionnaire on a web site or banners on a web site with an invitation to participate in a survey. A web-based survey may potentially be very useful when the purpose is to investigate something closely related to the web site including user-characteristics. Some advantages of web-based surveys are: the sample is selected (drawn) directly from a sub-population of the real users, they are interviewed when using the web site, and they are an inexpensive way of collecting data. An important feature of such surveys is the fact that the respondents are sampled proportional to how often they use the web site. However, these sampling probabilities are not easily available. When someone is logging onto a web site, the IP-address of the visitors' computer is registered, but this can not be used to uniquely identify visitors or their frequency of using the web site (see Pitkow 1997 for a discussion). In future research we plan to use so called cookies to get more detailed information of individual user frequency, but such information was not available in the present study.

It is important that the web-survey doesn't disturb the regular use of the web site. Therefore it is desirable that a visitor has the option to use the web site without filling out the questionnaire. However, this may lead to a very low response rate, and the sample of respondents may be

biased due to self selection. Hence, the question of how to deal with the potential bias in such surveys becomes an important issue. Our solution in this paper is to perform an additional survey, for instance by telephone, with a higher response rate and a lower degree of self selection, and to combine the two surveys by statistical modelling.

This approach is used in a study where data were collected both by web and by telephone. The purpose of the study was to investigate the users' opinions of a specific web site called ODIN. A web-based survey seemed to be a very useful way to collecting information about the web-users needs, since the sample could be selected directly from the sub-population who use the web site. However, there were as many as 88% non-respondents in the web-sample. There was no available information about the non-respondents, and one could not exclude the possibility that the non-respondents had a totally different opinion to the respondents. Especially, the willingness to respond may be higher among satisfied users of ODIN than dissatisfied users. Therefore, it was dangerous to draw conclusions from the observed web data only. For the purpose of studying this potential bias, a telephone survey was also carried out. In this data set, the number of non-respondents was negligible (see Section 2 for a discussion), but only 5% (55 people) of the sample had used the ODIN web site. Hence, telephone interviewing alone is a quite inefficient and expensive way of collecting information from the users of a particular web site, even if the web site is quite popular.

It may be possible to get a higher response rate than 12%, for instance by using incentives, but we believe that a low response rate should be expected in many web-based surveys. It only takes one click not to participate, normally a reminder cannot be send to the visitor, and answering is voluntary. We have also experienced a similarly low response rate on two other occasions when not using any incentives

This article is organized in the following way: Section 2 gives an overview of the two surveys, including results from a separate analysis of each survey. In Section 3 we discuss how the two surveys are related to each other as a consequence of their sampling schemes. Section 4 introduces a statistical model which allows the probability for non-response to depend on the respondents' opinion of the web site. Then the results, the estimates generated by the model, are presented (Section 5).

2 A pilot-study with a web-based survey and a telephone survey

The Norwegian Government's official web site is named ODIN (http://odin.dep.no/html/english/). In 1997 the use of this web site was analysed. One of the surveys was web-based. The other relevant survey for this paper was a telephone survey. The two surveys are:

- A pop-up questionnaire on the web site ODIN with 130 respondents, and 1000 non-respondents.
- A national telephone survey with 1012 respondents, constituting a random sample of the Norwegian population.

The web questionnaire remained available for 35 hours and no incentives were used. Every 20th visitor to ODIN was intercepted and received a questionnaire with 14 questions. The web-questionnaire popped up at the beginning of the ODIN session, but users were allowed to save the questionnaire and answer it after they had finished the visit. According to the log-file 1130 users (robots & search engines were subtracted) received the web-questionnaire, and almost all of these were Norwegians (with the extension ".no" in the IP-address). In the following we neglect the small proportion of foreign users and assume that all users are Norwegian.

The telephone data were collected by Gallup Norway, according to their ordinary sampling routines. There are non-respondents in these data too (about 30%). However, compared to the web-survey, it is much less likely that the response rate is directly related to the users' opinion about ODIN. The response rate may vary systematically with certain criteria such as sex and age, but the population averages of these criteria are known exactly for the total Norwegian population. One may therefore correct for bias related to these criteria by down-weighting groups which are over-represented in the sample compared to the population total (see for instance Särndal, Swensson and Wretman 1992), and the missing observations may be ignored. Usually, Gallup Norway performs such weighting according to sex, age and place of residence. However, this had little practical importance for the present sample. Hence, for simplicity we have ignored the weighting, and assume that the respondents were randomly chosen from the Norwegian population.

The non-response in the web data is much more serious, and can not be ignored. First, it is reasonable to assume that the response rate is systematically related to the questions under investigation, namely the users' opinion about the web site and their frequency of using it. Second, the response rate is very low. Third, there is no exact information on population level to correct for bias. However, the telephone data contain relevant, but uncertain information, which calls for a combined analysis of the two data sets.

In both surveys, the respondents were asked how often they visited the web site. In the telephone survey they had these alternatives: "never", "once", "few", "periodically", "monthly", "weekly" or "daily". The respondents of the web survey were given only the last six alternatives, since by definition they had used ODIN at least once. People who had never used ODIN are in the following defined as NON-ODIN users. These are said to belong to category 0. An ODIN user is defined as a person who had used ODIN at least once.

The ODIN users were further asked how useful ODIN was to them, with alternatives "not useful", "little usefulness", "some usefulness", or "very useful". For the present analysis, the classifications are simplified, such that we only distinguish between *satisfied* and *less satisfied* users, and between *frequent* and *less frequent* users. A satisfied user is here defined as one who has found the web site "very useful", whereas all others are classified as less satisfied. A frequent user is defined as one who uses ODIN "daily" or "weekly". The ODIN users are then cross-classified into the following four categories:

category 1: less frequent (LF) and less satisfied (LS) users
category 2: frequent (F) and less satisfied (LS) users
category 3: less frequent (LF) and satisfied (S) users
category 4: frequent (F) and satisfied (S) users.

In the telephone data set, the 55 ODIN users are classified into one of the categories 1 to 4, whereas the remaining people (used ODIN "never") are classified into category 0. In the web data set, 1000 out of 1130 people refused to answer the questionnaire. These 1000 people are considered as missing observations. The remaining 130 people were classified into one of the possible categories 1 to 4. Table 1 shows the numbers within each category for the two data sets.

Insert Table 1 around here

3 Relating the two data sets - un-weighted and weighted proportions

In this section we discuss the different sampling properties of the two surveys. From this we define *un-weighted* and *weighted* proportions of satisfied users and of frequent users.

Consider first the people reached by the telephone survey. Let p_i, i=0, ... , 4 be the probability that such a person belongs to the i-th category, i.e.

$$p_i = P\text{(person reached by phone belongs to category i)} \quad i = 0, \ldots, 4. \qquad (1)$$

Next, consider the web survey. Let q_i denote the corresponding probabilities

$$q_i = P\text{(person reached by web belongs to category i)} \quad i = 1, \ldots, 4. \qquad (2)$$

One could also define q_0= P(person reached by web belongs to category 0), but this probability is exactly zero. The rationale behind the use of different probabilities for the two data sets is that the sampling procedure differs between the two surveys. In both surveys, the people are sampled from the total Norwegian population. In the telephone survey, each person is sampled with equal probability, while in the web survey each person is sampled proportionally to their frequency of using ODIN. If a person uses ODIN daily for example, the probability of getting the web-questionnaire would be about 30 times higher than if they accessed ODIN on a monthly basis.

The next step in the modelling is to introduce dependency between $(p_0,\ldots,p_4)$, and $(q_1,\ldots,q_4)$ which are of course related parameters. Consider the total population, and let n_i denote the number of people in the i-th category. Let w_{ij} , j=1, ... , n_i be weights proportional to the frequency of using ODIN by the j-th person of category i. The sampling schemes then link the p- and q-probabilities together through

$$q_i = (1/n_i)\sum_{j=1}^{n_i} w_{ij}\, p_i = w_i\, p_i, \quad i = 1,\ldots,4. \qquad (3)$$

where w_i is proportional to the average frequency within category i. The w_i's are normalized such that $\sum q_i = 1$.

The definitions of p_i and q_i in (1) and (2) follow from the sampling schemes. However, they have also alternative interpretations:

- p_i is the proportion of the total population that belongs to category i, i=0, ..., 4.
- q_i is the corresponding *weighted* proportion, where each person is weighted proportionally to their frequency of using ODIN.

We are interested in the proportion of people within each category, and especially some marginals: those of frequent users and of satisfied users among all ODIN users. The *un-weighted* proportion of satisfied users is defined by

$$\frac{\text{number of satisfied ODIN users}}{\text{all ODIN users}}$$

$$= (p_3 + p_4)/(p_1 + p_2 + p_3 + p_4) \quad . \quad (4)$$

The corresponding *weighted* proportion of satisfied users is defined by

$$\left(\sum_{i=3}^{4}\sum_{j=1}^{n_i} w_{ij}\right) \Big/ \left(\sum_{i=1}^{4}\sum_{j=1}^{n_i} w_{ij}\right)$$

$$= (q_3 + q_4)/(q_1 + q_2 + q_3 + q_4) \quad . \quad (5)$$

The *un-weighted* and *weighted* proportions of frequent users are defined similarly.

Both *un-weighted* and *weighted* proportions are interesting quantities. If the purpose is to improve a web site, it may be more important to satisfy frequent users' than "surfers", and *weighted* proportions are then meaningful. On the other hand, less frequent users may become frequent users in the future if the web site is improved according to their needs, therefore the *un-weighted* proportions are also of interest.

Since people in the telephone survey are sampled with equal probability, the un-weighted proportion of satisfied users may be estimated from the telephone data set alone, using a sample version of (4) to the telephone data. The estimated proportion of frequent users is (10+3)/55, and the estimated proportion of satisfied users is (8+3)/55. The estimates and their 95% confidence intervals are shown in Table 2.

Insert Table 2 around here

The confidence intervals are calculated by bootstrapping (Efron and Tibshirani 1993): An artificial data set is created by random draws of 55 observations with replacement from the original data set, and a new estimate is calculated from this artificial data set. This is repeated 4000 times, yielding 4000 artificial estimates which will vary over the data sets. These estimates are used to calculate the confidence intervals by the bias corrected percentile method (Efron 1982).

Consider then the web-based survey, and assume for the moment that it is completely random who answered and who did not. Then the *weighted* proportion of satisfied users can be estimated simply by using the sample version of (5) on the web data, without knowledge of the individual frequencies w_{ij}.This is because the ODIN users in the web-based survey are sampled proportional to their frequencies w_{ij}. The result is presented in Table 3. The *weighted* proportion of frequent users is 38%. This is higher than the *un-weighted* proportion of 24% in Table 2, and reflects the fact that in the web-based survey the frequent users by definition are sampled more often than the less frequent ones. However, this is a relatively small increase: Let us assume that the frequent users log onto ODIN 10 times more often than the less frequent users. An *un-weighted* proportion of 24% frequent users would then correspond to a *weighted* proportion of (10 x 0.24) / (1 x 0.76 + 10 x 0.24) = 76%. Hence, one can wonder if the frequent users are under-represented among those who answered the web-questionnaire.

Insert Table 3 around here

In general, inference based only on the observed answers could be very misleading exactly because the probability of a user not responding may depend on which of the categories they belong to, and especially if the user is satisfied or not. Hence, to get reliable results for the *weighted* proportions, it is essential to perform a combined analysis of the two data sets. This will be the theme of the next section.

4 A statistical model for combining the surveys, allowing for non-ignorable non-response

In this section, we will drop the assumption that non-response was completely random, and allow the response rate in the web survey to differ systematically between satisfied and less satisfied users, and between frequent and less frequent users.

However, in order to reduce the number of parameters to be estimated, we will first assume some more structure in the relationship between the two data sets as defined in (3). Members of categories 1 and 3 are less frequent users, and it is reasonable to assume that the average use is approximately the same in the two categories. To be parsimonious we therefore assume $w_1 = w_3 = w_{LF}$, and for the same reason we assume $w_2 = w_4 = w_F$. By definition, we have that $w_{LF} < w_F$ or equivalently $w_F / w_{LF} > 1$. Now, p_i and q_i are linked together through

$$q_1 = w_{LF} p_1 \quad , \qquad q_2 = w_F p_2 \quad ,$$

$$q_3 = w_{LF} p_3 \quad , \qquad q_4 = w_F p_4 \quad . \qquad (6)$$

Since both the p_i and q_i probabilities add to one, there are now 5 free parameters to be estimated. It is for instance sufficient to know p_1, p_2, p_3, p_4 and the ratio w_F / w_{LF}. Then p_0 is given by $p_0 = 1 - p_1 - p_2 - p_3 - p_4$, whereas w_{LF} and w_F are given by $w_{LF} = 1/[p_1 + p_3 + (w_F / w_{LF})(p_2 + p_4)]$ and $w_{LF} = w_{LF}(w_F / w_{LF})$, which follows from (6) and from $\sum q_i = 1$.

We now introduce a logistic regression model for non-response in the web sample, where the probability of response may depend on the category. A model with one specific probability of response for each category would be impossible to identify. Instead, we postulate a logistic regression model where the linear predictor includes main effects, but no interactions. Let r_i be the probability of response for a user in the i-th category. Our response model is then defined by

$$\log\left(\frac{r_i}{1-r_i}\right) = \begin{cases} \beta_1 & \text{if } i = 1 \\ \beta_1 + \beta_F & \text{if } i = 2 \\ \beta_1 + \beta_S & \text{if } i = 3 \\ \beta_1 + \beta_F + \beta_S & \text{if } i = 4 \end{cases} \quad . \qquad (7)$$

The parameter can be expressed as $\beta_F = \log([r_2/(1-r_2)]/[r_1/(1-r_1)])$ $= \log([r_4/(1-r_4)]/[r_3/(1-r_3)])$ which is the log odds ratio of the probability of response between frequent and less frequent users. The parameter β_S has a similar interpretation as the log odds ratio of the probability of response between satisfied and less satisfied users. The response probabilities may also be expressed directly, for instance as $r_1 = (\exp(\beta_1))/(1+\exp(\beta_1))$.

The full model has 8 free parameters to be estimated. Denote these parameters by θ, where $\theta = \{p_1, p_2, p_3, p_4, w_F / w_{LF}, \beta_1, \beta_F, \beta_S\}$.

The telephone data are multinomial with probabilities, $p_0, \ldots, p_4$, and is thus directly related to θ. It remains to establish the relationship between θ and the web data. The web data are multinomial with 5 categories. Let Q_i, i=1, ...,4 denote the probability of a person responding *and* belonging to the i-th category, and let Q_5 be the probability of not responding (missing). These probabilities are given by

$$Q_1 = r_1 q_1 \quad , \quad Q_2 = r_2 q_2 \quad , \quad Q_3 = r_3 q_3 \quad ,$$

$$Q_4 = r_4 q_4 \quad , \quad Q_5 = 1 - \sum_{i=1}^{4} Q_i \quad . \qquad (8)$$

The model is now fully specified. Let x_i, i=0, ..., 4 and y_i, i=1, ..., 5 denote the observed numbers within each category in the telephone and web data respectively (from Table 1). Except for a constant independent of θ, the log likelihood is ℓ where

$$\ell = \sum_{i=0}^{4} x_i \log(p_i) + \sum_{i=1}^{5} y_i \log(Q_i) \quad , \qquad (9)$$

since the two data sets are independent and multinomial. The maximum likelihood estimate of θ is found by maximizing (9) by a numerical optimization procedure. Several constraints apply to the various single parameters in θ, so in order to simplify the numerical optimization the parameters in θ are transformed to 8

unconstrained parameters. The transformations are shown in Appendix A.

Confidence intervals are found by bootstrapping as in Section 3. New artificial data sets are constructed in pairs by independent random sampling with replacement from both the telephone and web data sets.

5 Estimation results assuming non-ignorable non-response

We now return to the model defined in the last section that is based jointly on both samples. The estimated parameters are given in Table 4, including some derived parameters. We see that satisfied users are significantly more willing to answer the web-questionnaire than less satisfied users (the estimated log odds ratio β_S is significantly positive), which seems to be very reasonable. The estimate of β_F is negative, which is interpreted as a lower probability of response among frequent users than among less frequent users, but this effect is not significant. The estimate of w_F/w_{LF} is 10, which is interpreted as frequent users using ODIN on average ten times more often than less frequent users. This is a reasonable result, but the uncertainty is large, and the estimate is not significant different from 1. Hopefully, we will be able to get more precise estimates in later studies, because we plan to collect more detailed information of individual user frequency by using cookies, and we also plan to increase the sample sizes of both types of data.

Insert Table 4 around here

The new estimates of the *un-weighted* proportions are given Table 5, which should be compared to Table 2. The point estimates are unchanged (within the accuracy shown in the tables). Thus, combining the data sets has *not* given more precise estimates of the *un-weighted* proportions. The reason is that there are *too* many missing observations in the web sample to influence the estimates of the *un-weighted* proportions.

Insert Table 5 around here

Table 6 gives the estimates for the *weighted* proportions, using both data sets. These results are quite different from those we got from the observed web data only (Table 3). The estimated *weighted* proportion of frequent users has changed from 38% in Table 3 to 76% in Table 6. The estimate of the *weighted* proportion of satisfied users is now 22%, compared to 48% in Table 3. This gives a much less positive impression of the usefulness of ODIN than the numbers in Table 3, which were calculated under unrealistic assumptions. The confidence intervals are larger in Table 6 than in Table 3, because they are based on more realistic assumptions. Our statistical model allows that the probability of answering depended on the users' frequency and satisfaction.

Insert Table 6 around here

6 Concluding remarks

Internet as a medium presents certain unique problems for surveying. Since there is no central registry and it is neither practical nor affordable to contact all users of Internet, a basic challenge is to develop methodologies and research strategies that may produce statistically reliable data based on a selection of subsets of users. Data from web-based surveys must be interpreted with care; often the statistical value is limited.

Our research strategy has been to combine data from a web-based survey with data from another survey with fewer data, but with better control of the response rate and self selection. Our initial web-based survey had a predictably low response rate, and although the results from this survey gave valuable information about the actual web site, we have seen the need for more rigorous statistical analysis. The combination of the data set from the web-based survey with data from a nation-wide, representative survey of the same site gave more reliable results. However, the current study is based on a simple schematization of realistic surveys. Firstly, we have assumed that the telephone survey was an ideal representative random sample, but in reality such surveys may have defects that require more sophisticated modelling. Further, we have considered only two response variables of interest, each one with only two levels. With more variables, more categories and perhaps continuous, but non-Gaussian variables, the model would become much more complex and difficult to estimate.

Some conclusions may be drawn from our analysis. Firstly, web-based surveys can become a valuable tool in market research, but the methods and techniques must be further developed in order to get more valid information about the users of a web site. There is little doubt that this kind of survey offers unique time

and cost benefits for market researchers. Our approach with a pop-up questionnaire to every 20th visitor, where the responses are immediately sent back to our server and stored in our database ready for the analysis, has demonstrated some of these benefits. Secondly, since the response rate is often quite low and there is a lack of information about the non-respondents, we recommend that web-based surveys should be combined with parallel surveys in order to validate the data sets and get better control of responses and respondents. The results from our analysis indicate that the biases in web-surveys can be substantial, and that therefore some kind of alternative or complementary strategy is not only recommended, but probably necessary. Moreover, our strategy has been shown to be fruitful in minimizing the biases due to a high non-response rate in the web-based survey.

Lastly, and contrary to recent research, our results shows statistically significant positive correlation between satisfaction and response rate. Peterson & Wilson (1992) conclude that satisfaction percentages are not related to response rate percentages. The basis for their conclusion is a correlation test of 15 independent studies containing both satisfaction percentages and response rates percentages. Our approach is different. We have two samples from the same population, and this gives us a unique opportunity to analyse user attitudes more accurately. As also stated by Peterson and Wilson, the concept of satisfaction is difficult to analyse due to lack of standardisation. Also it may reflect the Hawthorne effect: attempts to measure customer satisfaction will often, in and of themselves, increase satisfaction, regardless of the product or service being investigated. Here our approach, which combines different data sets of the same population, may present an interesting alternative methodological strategy to simple correlation tests of quite different and often incompatible issues, populations and concepts of satisfaction.

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Appendix A Reparameterization

Here we reparameterize the 8 constrained parameters of θ into 8 unconstrained parameters, to simplify the numerical optimization. Let a_i, i=1, ..., 4 be unconstrained parameters, and let p_i, i=1, ..., 4 be defined by

$$p_i = \exp(a_i) \Big/ \left(1 + \exp\left(\sum_{i=1}^{4} a_i\right)\right) \quad . \qquad (10)$$

To assure that the ratio w_F / w_{LF} is greater than 1, it is reparameterized as

$$w_F / w_{LF} = 1 + \exp(b) \quad . \qquad (11)$$

Now, estimates of $\theta = \{p_1, p_2, p_3, p_4, w_F / w_{LF}, \beta_1, \beta_F, \beta_S\}$ can be found by estimating the unconstrained parameters $\{a_1, a_2, a_3, a_4, b, \beta_1, \beta_F, \beta_S\}$.

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Tables

Table 1 Number of people within each category in the two data sets.

Category	0	LF-LS 1	F-LS 2	LF-S 3	F-S 4	missing
Telephone survey	957	34	10	8	3	-
Web survey	-	48	20	32	30	1000

Table 2 Estimated proportion of frequent and satisfied users, based on the telephone data only. 95% confidence intervals are given in parenthesis.

Proportion of frequent users	24% (14-36)
Proportion of satisfied users	20% (11- 32)

Table 3 Estimated weighted proportion of frequent and satisfied users, based on the observed web data only. 95% confidence intervals are given in parenthesis.

Weighted proportion of frequent users	38% (30-47)
Weighted proportion of satisfied users	48% (39- 56)

Table 4 Estimated parameters with 95% confidence intervals, based on both samples.

parameter	estimate	lower 95% conf.lim.	upper 95% conf.lim.
p_0	94.6%	93.2%	95.8%
p_1	3.4%	2.3%	4.5%
p_2	1.0%	0.5%	1.7%
p_3	0.8%	0.4%	1.4%
p_4	0.3%	0.0%	0.6%
w_F/w_{LF}	10.1	1.0	44.8
β_1	-1.29	-2.87	1.22
β_F	-2.17	-4.92	1.19
β_S	1.74	0.52	3.62
r_1	21.6%	5.4%	77.3%
r_2	3.0%	1.5%	17.2%
r_3	61.1%	14.4%	100.0%
r_4	15.2%	3.7%	31.7%

Table 5 Estimated proportion of frequent and satisfied users, based on a combined analysis of both samples. 95% confidence intervals in parenthesis.

Proportion of frequent users	24% (14-36)
Proportion of satisfied users	20% (11- 32)

Table 6 Estimated *weighted* proportion of frequent and satisfied users, based on a combined analysis of both samples. 95% confidence intervals in parenthesis.

Weighted proportion of frequent users	76% (17-92)
Weighted proportion of satisfied users	22% (11- 41)