**INTRODUCTION**

It has been extremely popular for many years to conduct marketing research and to give recommendations based on drawn conclusions in order to better manage organisations or to reach potential customers. However, in order to be sure that the conducted marketing research is reliable and accurate, it is also necessary to look at the methodology of the research. Issues that the researcher should consider as a part of the research process include ways of selecting the research sample, data collection techniques, and correct translation of business questions into research questions and hypotheses.

However, in addition to the aspects mentioned above, an extremely important yet often overlooked issue, is analysis of missing data. It is important to do so because the existence of missing data entails potential risks. Due to the occurrence of missing data, reduced sample sizes may lead to biased estimators, lower statistical power of the analyses, problems in estimating confidence intervals, or type I or II errors in statistical inference [Collins et al. 2001, p. 330].

Recognising the gap in the area of missing data analysis in surveys, the author of this article would like to present an analysis of the randomness of missing data before analyzing the collected data.

**TYPES OF MISSING DATA**

Missing data that occur during the collection of data for analysis can be divided into a few categories. The first category is data deficiencies, which in the literature is called unit non-response. Their occurrence results from the inability to conduct a questionnaire interview with a person selected to participate in the study. One reason for this may be that the potential respondent refuses to participate in the survey. The way to deal with this type of situation is the weighting procedure [Durrant 2005, p. 3].
The second reason for the occurrence of missing data may be the omission of potential respondents in the sampling frame. In this case the weighing procedure can be also used to deal with the existing missing data [Brick and Kalton 1996, p. 216].

The third type of data deficiency is referred to as item non-response. In this case, the person drawn to participate in the study agreed to participate but for various reasons decided not to answer individual questions in the survey questionnaire. Ultimately, the analysed data set contains various variables with missing data for individual observations. In this case the answer to this situation can be an analysis of complete observations or the application of different methods of imputing the missing data [Durrant 2005, p. 3, Shaharudin et al. 2020, p. 646]. This means using such statistical methods that allow to replace the missing data by some value calculated on the basis of the data set held, or by the actual value of an observation that occurs in the data set [Dunn 1997, p. 161]. Multiple imputation of missing data is a method of imputation commonly used in research [Siddique et al. 2012].

When analysing data deficiencies, two aspects can be distinguished: patterns of data deficiencies and mechanisms for generating data deficiencies. The first of these refers to the configuration of values and missing data observable in the data set. Mechanisms, on the other hand, describe the relationship between variables and the probability of missing data [Enders 2010, p. 3–4].

In Figure 1 shows the types of missing data occurrence. The rectangles denote variables in the data set. Black colour indicates missing data occurrences.

Fig. 1. Patterns of occurrence of missing data
Source: Prepared by [Enders 2010, p. 4].
The first pattern is the univariate pattern, which illustrates a situation where missing data occur in a data set in a single variable. It may appear in the case of experimental studies [Enders 2010, p. 4–5].

In the second pattern, missing data do not appear in variables $Y_1$ and $Y_2$, as all respondents answered both questions. However, missing data appear in $Y_3$ and $Y_4$. This pattern is called the unit non-response pattern and often occurs in survey research [Enders 2010, p. 4–5].

Another pattern, monotonous missing data, represents a situation where, for some reason, participants stop participating in the study over time. It often occurs in the case of longitudinal studies [Enders 2010, p. 4–5]. In the literature this problem is referred to as panel depletion [Babbie 2004, p. 124].

General missing data is a pattern in which missing data occur in different variables of a data set. At first glance, the missing data generation mechanism appears to be random, although in reality it is not necessarily so [Enders 2010, p. 405].

Another pattern, called by Enders planned missing data pattern, illustrates the case where missing data are planned and controlled by the researcher. The purpose of planned missing data is to reduce the burden on the respondents to participate in the survey, as well as to reduce the cost of conducting the survey [Enders 2010, p. 4–5]. One way to create planned missing data is to use the three-from design method proposed by Graham et al. The study asks four sets of questions: $X, A, C$ and $D$. The three versions of the survey questionnaire are the result of combinations of these groups of questions. However, each version of the questionnaire includes the $X$ question set, which contains the most important questions of the research [Graham 2012, p. 282].

The last pattern is the latent variable pattern, in which latent variables are treated as those with missing data. An exemplification of such a variable can be a latent construct in factor analysis, which explains the relationships between observable variables. However, the factor itself has missing data for all observations because it cannot be measured [Enders 2010, p. 4–5].

### MECHANISMS FOR GENERATING MISSING DATA

#### Missing Completely at Random (MCAR)

Rubin distinguishes three types of missing data. The first of these is called Missing Completely at Random. Missing data in this case are generated by a completely random mechanism. MCAR-type missing data occurs when the existence of missing data in an observation for a particular variable is not linked to the value of that observation, nor to the value of any other variable [Allison 2002, p. 3, Padgett et al. 2014, p. 2]. Hence, it can be said that the probability of missing data is completely independent of the data [Newman 2014, p. 376].

If the above condition is met for all variables in the data set under consideration, the data set is a simple random sample of such a data set in which all observations that are missing would have specific observable values [Baraldi and Enders 2010, p. 7].

Thinking about the MCAR missing data generation mechanism, one can imagine generating missing data in a way similar to tossing a coin, where heads would indicate the occurrence of a certain value in a variable and tails would indicate the occurrence of missing data [Graham 2012, p. 13].

Table 1 contains three variables: respondent’s ID, job experience and income. The original data were supplemented in such a way as to present the mechanisms of generating missing data: MCAR, MAR and NMAR.

If missing data are generated by the MCAR mechanism then the probability of missing data does not depend on the respondent’s income.

\[
P(X|D = 2500) = 1/4 \\
P(X|D = 3000) = 2/8 = 1/4 \\
P(X|D = 5000) = 1/4
\]

In this situation, the probability of missing data occurrence does not depend on the length of job experience either.

\[
P(X|S = 0) = 2/8 = 1/4 \\
P(X|S = 5) = 2/8 = 1/4
\]

In order to rule out the hypothesis that missing data are generated completely at random, specific
Table 1. Data set with information on job experience and income of the respondent, presenting different mechanisms of generating missing data

| Respondent’s No. | Job experience (S) | Income (D) | MCAR | MAR | NMAR |
|------------------|--------------------|------------|------|-----|------|
| 1                | 0                  | 2500       | 2500 | 2500| 2500 |
| 2                | 0                  | 2500       | 2500 | 2500| 2500 |
| 3                | 0                  | 2500       | \times | 2500 | 2500 |
| 4                | 0                  | 3000       | 3000 | 3000| \times |
| 5                | 0                  | 3000       | \times | 3000 | 3000 |
| 6                | 0                  | 3000       | 3000 | 3000| 3000 |
| 7                | 0                  | 3000       | \times | 3000 | 3000 |
| 8                | 0                  | 3000       | 3000 | 3000| 3000 |
| 9                | 5                  | 3000       | 3000 | \times | 3000 |
| 10               | 5                  | 3000       | 3000 | 3000| 3000 |
| 11               | 5                  | 3000       | 3000 | 3000| 3000 |
| 12               | 5                  | 3000       | 3000 | 3000| 3000 |
| 13               | 5                  | 5000       | 5000 | \times | 5000 |
| 14               | 5                  | 5000       | 5000 | 5000| \times |
| 15               | 5                  | 5000       | \times | \times | \times |
| 16               | 5                  | 5000       | 5000 | 5000| 5000 |

Source: According to [Allison 2002]. Own prepared in cooperation with prof. Szymon Czarnik.

Statistical tests can be used. The first of these, relating to individual variables, is the Student’s t-test for independent samples. The test is performed by dividing the observations of a variable into observed values and missing data, and then checking the difference in means between groups within another variable. A non-significant Student’s t-test means that there are no statistically significant differences in means between groups, which is consistent with the assumption that missing data are generated by a completely random mechanism [Enders 2010, p. 18–19].

Another way to check whether the missing data generation mechanism is of the MCAR type is to perform the Little’s Test. This is a general test and its calculation takes into consideration differences in the mean for all the variables in the analysis [Enders 2010, p. 19–21].

The next way to assess whether missing data are randomly generated is to check the correlation of missing data for selected pairs of variables. If the correlation between the variables is low, then it can be assumed that missing data are random [Tsikriktsis 2005, p. 56].

The last way to assess the randomness of missing data is to use a regression model [Pigott 2001, p. 360]. Some authors claim, however, that there is no possibility to assess the randomness of missing data at all [Lang and Little 2014, p. 6–7].

### Missing at Random

The second mechanism for generating missing data mentioned in the literature is Missing at Random (MAR). Missing data are considered to be of MAR type if the probability of missing data on variable $Y$ is uncorrelated with the unknown value of observations on variable $Y$, while controlling for other variables in the analysis [Allison 2002, p. 4]. The randomness of missing data occurs in association with categories of other variables in the data set. This means that there is a systematic relationship between the variable in which the missing data occur and the probability of missing data [Padgett et al. 2014, p. 2].

Referring to the example presented in Table 1, it can be said that if the missing data are generated by the MAR mechanism, the probability of missing data can (and in this case does) depend on the amount of income.

- $P (X|D = 2500) = 0$
- $P (X|D = 3000) = 2/8 = 1/4$
- $P (X|D = 5000) = 2/4 = 1/2$
The probability of missing data may (and in this case does) depend on the job experience.

\[ P(X|S = 0) = 0 \]
\[ P(X|S = 5) = \frac{4}{8} = \frac{1}{2} \]

However, the probability of missing data cannot both depend and not depend on the amount of income while controlling for the job experience variable.

For job experience of 0 years, the missing data are equally likely to occur for respondents earning PLN 2500 and PLN 3000; and for job experience of five years, the missing data are equally likely to occur for respondents earning PLN 3000 and PLN 5000.

For job experience of zero years:
\[ P(X|D = 2500) = 0 \]
\[ P(X|D = 3000) = 0 \]

For job experience of 5 years:
\[ P(X|D = 3000) = \frac{2}{4} = \frac{1}{2} \]
\[ P(X|D = 5000) = \frac{2}{4} = \frac{1}{2} \]

Comparing the mechanisms for generating missing data discussed so far, it is worth mentioning that MCAR-type missing data meet the assumptions for MAR missing data [Allison 2003, p. 545].

**Not Missing at Random**

The last mechanism for generating missing data described by Rubin is the Not Missing at Random mechanism. Missing data will be identified as generated by a completely non-random mechanism when the occurrence of missing data for a specific variable is related to the value of observations on this variable, even when controlling for other variables [Enders 2010, p. 8, Padgett et al. 2014, p. 2].

In the example presented in Table 1, the missing data mechanism is NMAR when the probability of missing data depends on income.

\[ P(X|D = 2500) = 0 \]
\[ P(X|D = 3000) = \frac{2}{8} = \frac{1}{4} \]
\[ P(X|D = 5000) = \frac{2}{4} = \frac{1}{2} \]

The probability of missing data does not depend on the job experience of the respondent.

\[ P(X|D = 3000) = \frac{2}{8} = \frac{1}{4} \]
\[ P(X|D = 5000) = \frac{2}{8} = \frac{1}{4} \]

In this case, even when controlling for job experience, the probability of missing data depends on the amount of income.

For a job experience of zero years, the probability of missing data is different for incomes of PLN 2500 and PLN 3000.

\[ P(X|D = 2500) = 0 \]
\[ P(X|D = 3000) = \frac{2}{4} = \frac{1}{2} \]

For a job experience of five years, the probability of missing data is different for incomes of PLN 3000 and PLN 5000.

\[ P(X|D = 3000) = 0 \]
\[ P(X|D = 5000) = \frac{2}{4} = \frac{1}{2} \]

The problem here, which is related to the existence of non-random missing data in the analyses, is the generation of loaded estimators which differ from the parameters in the population by a systematic error [Graham 2009, p. 553].

**METHODOLOGY AND RESULTS**

When reviewing the available data sets, it can be observed that some variables generate more missing data than others. The question generating potential problems related to the existence of missing data in the PGSS concerns the respondent’s income. In 1995, the question about average monthly income was not answered by 1.9% of the respondents. In the last years of the survey, the number of missing data increased to 5.6% for the 2008 survey and 6.2% for the 2010 survey, respectively.

An analysis of missing data was performed on the example of the variable income from work of the PGSS conducted in 2008. In order to check whether the missing data in the income variable are completely random, the Student’s t-test for independent samples was performed. The income variable was divided into two sets of data – those respondents who answered the income question and 

1 Respondents who were not working during the survey were excluded from the missing data analysis.
those who did not answer the question. The responses of the respondents who did not work during the survey, and thus had no income, were excluded from the analysis. Nine respondents whose income differed from the income of other respondents were also excluded from the analysis.

In order to check the average value for both groups on another variable that is correlated with the income variable, correlations were checked between the income variable and continuous variables that could be correlated with the income variable, i.e. the number of years of schooling, the number of years of income-generating work since the age of 14 and the size of the respondent’s dwelling.

The correlation turned out to be statistically significant for only one variable. This variable was the number of years of schooling of the respondent.

The group of respondents who answered the question about income from work was significantly larger than the group of respondents who did not answer this question. Taking into account this fact and the assumption of the Student’s t-test of the equality of the analysed groups [Bedyńska and Cyprańska 2013, p. 163], in further analyses observations with missing data were used and a sample was drawn from among the respondents who answered the question about income.

The differences in the mean for the two groups analysed were found not to be large, nor was the difference between the standard deviations (See Tab. 2). A non-significant Student’s t-test for independent groups means that it is impossible to reject the null hypothesis that missing data are generated by a completely random mechanism (See Tab. 3). In this situation, missing data can be treated as random.

Fig. 2. A histogram for the variable income from the respondent’s work
Source: Author’s own compilation.
CONCLUSIONS

The existence of missing data is a challenge for many analysts and researchers conducting surveys. The best way to avoid large missing data is to design your survey carefully [Allison 2002, p. 2–3].

If, however, a significant number of missing data is present in a data set, the next step should be to verify the randomness of the missing data. For this purpose, it is worth using statistical tests, i.e.: Student’s t-test for independent samples and the Little’s Test. If the mechanism for generating missing data is not completely random, it is worth considering potential variables that are correlated with the variable having missing data. The theory or results from the existing studies may help to identify these variables [Enders 2010, p. 17].

The omission of data gap analysis in research and methodological reports may lead to inadequate research conclusions and recommendations. Even if

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**Table 2.** Pearson correlation coefficients between respondent’s income from work and other variables included in the Polish General Social Survey 2008

| Specification                  | Size of the respondent’s dwelling | Years of schooling | Years of work experience since the age of 14 |
|-------------------------------|-----------------------------------|--------------------|---------------------------------------------|
| Respondent’s income PLN correlation | 0.69                              | 0.329              | 0.083                                        |
| Statistical significance      | 0.129                             | 0.001              | 0.063                                        |
| N                             | 478²                              | 509                | 507                                          |

Source: Author’s own compilation based on [ADS].

**Table 2.** Presentation of statistics – mean, standard deviation for groups: missing data and observable values

**Group Statistics**

|                   | N   | Mean  | Std. Deviation | Std. Error Mean |
|-------------------|-----|-------|----------------|-----------------|
| Years of schooling| 73  | 12.47 | 3.168          | 0.371           |
| missing data      | 75  | 12.63 | 2.782          | 0.321           |

Source: Author’s own compilation.

**Table 3.** Student’s t-test for two independent groups (missing data and observable values on the respondent’s work income variable) for the respondent’s length of job experience

| Author's own compilation. |
|---------------------------|

**2 Any outliers were excluded from the analysis.**
there appear to be few missing data in the data set, i.e. less than 3%, very often the purpose of the analyses performed is not to calculate statistics for a single variable but to perform multivariate analyses. In this case, it may turn out that, out of the whole sample, the analysis will be carried out on a much smaller number of observations that are in the data set [Allison 2002, p. 2].

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WYSTĘPOWANIE BRAKÓW DANYCH W BADANIACH ANKIETOWYCH

STRESZCZENIE

Celem niniejszego artykułu jest omówienie zagadnień związanych z analizą braków danych. Dlaczego braki danych występują w zbiorze danych? Ile procent zebranych danych stanowią braki danych? Jaka jest natura braków danych, które pojawiły się w trakcie zbierania danych? Jakie czynniki mogą wpłynąć na potencjalne pojawienie się braków danych? Powyższe pytania, na które autorka artykułu pragnie odpowiedzieć w jego ramach są niezwykle istotne w ocenie prowadzonych badań ankietowych lub ocenie jakości danych zastanych. Brak repleksji nad wspomnianymi powyżej aspektami może prowadzić natomiast do wyciągania fałszywych wniosków oraz rekomendacji. Stąd też analiza braków danych jest niezwykle istotnym, a często nadal pomijanym etapem analizy danych ankietowych. W ramach artykułu przestawiona została analiza losowości braków danych na podstawie danych zebranych w ramach Polskiego Generalnego Sondażu Społecznego w 2008 roku.

Słowa kluczowe: badania ankietowe, analiza braków danych, MCAR, MAR, NMAR