Making sense of missingness: Analyzing skipped items in engineering education research

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Abstract

Researchers who use online, survey-based study designs often find that participants leave some items unanswered. This can be problematic, as most inferential statistics assume that data are missing at random (MCAR, i.e., that missingness can't be predicted by any participant characteristics), and if not, test conclusions may be invalid[1]. However, data that shows systematic missingness is not automatically useless. This paper details some of the missingness analysis conducted on data from a national survey of engineering graduate students (EGS) and their identities, motivation, and experiences. Visual analysis, Little's MCAR, and logistic regressions are used to explore the missing data and the analytic process; flowcharts and code are provided for future researchers.

Keywords

Methodology, analysis, missing data, engineering graduate students, identity

Introduction

Missing data provides an ongoing challenge to researchers using survey methodology. The issue of missing data is often overlooked, even as the topic has received increased coverage in the social sciences, particularly from professional organizations and the literature[2,3]. There has been a call for journals to more consistently require authors to describe their missing data and the procedures followed,[4] but little information is provided to the community about what it is, how it affects analyses, how it should be controlled for and/or corrected, and how it should be discussed. Consequently, peer reviewers do not have the information necessary to critically review discussions of missing data, a particularly pressing issue in engineering education, where researchers come from many subjects, backgrounds, and schools of statistical analysis. Consequently, this paper features a quick review of missing data discussions and will provide a description of the procedures used to analyze missing data in a large, national survey of engineering graduate students. The goal of this paper is to provide a guide to the analytic process for other engineering education researchers, as well as to act as a reference for future discussions of the current project and its practices. In addition to the text of this paper, an example of the R code used will also be supplied in Appendix 1.

Defining Missing Data

Data can be missing at two levels: the unit, or the item.[5] Unit nonresponse indicates that a participant did not complete any of the survey items, while item nonresponse indicates that only some items were left unanswered (note that these criteria do not include items that were selectively displayed; e.g., they only saw the question if they answered 'Yes' to a previous item).

This paper will focus primarily on item nonresponse, as this form of missing data is pervasive in survey research, has subtle but significant effects on analyses, and is often handled improperly.

In addition to the two levels of missing data, there are three possible patterns within the missing data. These patterns look at the relationship between missing items and non-missing items, to determine if data is missing systematically. The first pattern, and the most desirable if data must be missing at all, is MCAR, or Missing Completely at Random. This pattern suggests that there are no relationships between observed and unobserved data, and item nonresponse occurred completely at random. Data MCAR are good candidates for either complete case analysis (e.g., dropping participants with missing data) or data imputation methods (e.g., estimating the missing values based on responses provided).[6]

The second pattern is MAR, or Missing at Random. Although the term sounds similar to MCAR, it indicates a more serious issue in the response pattern and suggests that the complete cases do not constitute a random sample. For example, international students may skip a question about mood (e.g., ‘How often have you felt blue in the past week?’) because they are confused by the idiom. As a result, these values will be missing more often for international students, but the value of the responses omitted will still be randomly distributed -- there will be no relationship between mood and missingness. Complete case analysis, whether achieved through pairwise or listwise deletion, will produce inaccurate results, and so the best practice is to use data imputation.[6]

The final pattern is MNAR, or Missing Not at Random. This pattern indicates that item nonresponse depends on the value or amount of the response. For instance, students who procrastinate more may skip survey items asking about procrastination due to a social desirability effect. Unaware of this, the researcher may choose to drop all participants with incomplete responses when analyzing whether procrastination predicts participants’ attitudes towards group-work. They find no relationship with the incomplete dataset and move on to other research questions. However, these conclusions do not accurately reflect the relationship population (as seen by analysis with the full dataset), and so the negative relationship between procrastination and group-work attitudes it is not detected (type 2 error, or false negative). This is the most troubling of the patterns and the most difficult to resolve, but also has the most implications for psychological and educational research. Data imputation can be used with data MNAR, but the procedure is often as complex as the actual analysis the data was collected to run, and highly subject to criticism.[6]

To see an example of these missingness patterns visualized, see the graphs below (Appendix 2, Figure 1A-1E). Figure 1A shows the distribution of two simulated datasets with no missing values, and Figure 1B shows the same two datasets with data MCAR. Figure 1C shows the datasets with one group’s data missing randomly, e.g., data MAR. Figure 1D figure shows the dataset in which one group of participants with high scores had missing data, or data MNAR; Figure 1E plots the distribution of missing data of 1D alongside the full datasets to help visualize what the missing data looks like. The increasing dissimilarity between distributions indicates the ways in which missing data leads to misinterpretations of the populations and phenomena under study. Furthermore, Figures 1F and 1G show the relationship between ‘procrastination’ and ‘group work attitudes’ discussed above (using simulated data) with incomplete and complete datasets. With the complete dataset, the relationship is significant (β = -19.20, t = -2.47, p = .014; F(1,198) = 6.14, p = .014, *Adj.* R^2 = .03); with data MNAR, the relationship can no longer be detected (β = -14.88, t = -1.55, p = 0.122; F(1,171) = 2.42, p = .122, *Adj.* R^2 < .01).

Handling Missing Data

A 2003 review of the education literature indicated that analyses of missing data were improving, but did not yet follow best practices.[7] Specifically, only 15 studies discussed testing the patterns of missing data (e.g., whether it was missing randomly or systematically), and only 6 used maximum likelihood or multiple imputation to handle the missing values as recommended in the literature.[5,7] To help remedy this, recommendations from 8 sources were used to compile a decision-making flowchart (Appendix 3, Figure 2). In the following section, we will briefly outline the procedures in flowchart, with references to sources that go into more detail.[1,5–10]

1. **Check for unit nonresponse.** There are no concrete guidelines for what qualifies missingness as unit nonresponse, other than the vague rule that it renders a case unusable even as partial data. If unit nonresponse is an issue, proceed with weighting class adjustments or propensity scoring to acknowledge missingness at the group level.
2. **Check for item nonresponse.** Confirm that 5% of the data is missing due to item nonresponse. Again, this is not a rigidly enforced rule, and depending on the size and scope of your survey, may apply to some analyses but not others. Also use this step to explore visualizations of your missing data and see if patterns can be identified.
3. **Little's MCAR.** Little's MCAR is a chi-square test that checks for missingness completely at random across a group of items. As a chi-square test, it is sensitive to large sample sizes, and so caution may be needed when interpreting results. In R, the most frequently used package for Little's MCAR limits the number of items to 50, and so grouping may be needed to analyze an entire survey's worth of responses.
4. **Regression Analyses.** If Little's MCAR test is significant, it indicates that data is not missing completely at random. The next step is attempting to determine whether data is MAR or MNAR. More precise chi-squares and regression analyses can be used to explore whether key variables predict item nonresponse. Specifically, participants' responses to an item can be recoded dichotomously (either missing or non-missing) and a grouping variable (e.g., men and women or year in college) or a continuous variable can be used in a logistic regression to predict item nonresponse. If significant, this indicates a relationship between the two variables that can explain missingness. For instance, you might find that women are more likely to skip an age-related item, or participants' study skill scores and GPA may be related. It would not be sensible to analyze unrelated variables, and decisions about which variables to include will be driven by theory and should be reported.
5. **Determine MAR or MNAR.** The final step will potentially have the largest impact on your analyses but is also the one that has no predetermined path to follow. Determining MAR or MNAR requires investigation of the items that were skipped, the predictors, and theoretical considerations. If you determine that data are MAR, data imputation can be used (read more below). If your data are MNAR, data imputation can still be used, but a model must be created to predict and explain missingness. Even with multiple imputation to ameliorate missingness, any conclusions based on items MNAR must be interpreted cautiously.

The above represents an outline for how a missing data analysis could be conducted, based on recommendations from the literature. In the next section, we will describe this process as it unfolded for data collected by the GRADs project.

Data Imputation

There are several methods for handling data imputation. Mean imputation -- replacing the missing value with the item mean -- is the most straightforward, but also considered statistical malpractice.[11] Hot and cold deck imputation identify a participant similar to the one with the missing data and use their scores; hot deck imputation randomly selects a similar participant, while cold deck imputation uses a participant who is systematically chosen.[12] Interpolation and extrapolation are a similar procedure, in which a participant's other observations are used to estimate the missing data. The most frequently recommended method that is also highly accessible is regression imputation. This technique uses scores on correlated items to build a model of the relationship between items, and then uses the participants other responses to predict the missing data. In addition to regressions, other supervised and unsupervised learning techniques (K-nearest neighbors, Markov Chain Monte Carlo, and random forest algorithms) can be used to predict missing values. The specific techniques chosen often depend on the nature of the data, e.g., whether it is normally distributed, how many levels the variable has, etc.

Most of these techniques can be used once to predict a single substituted value (called single imputation). However, single imputation tends to underestimate error, which can become problematic when replacing many values in a dataset. As a solution, multiple imputation produces multiple estimates, thus more accurately accounting for error and showing less bias overall. Most missing data packages in R (mice, missForest, Hmisc, mi, Amelia, and BaBoon, among others) use multiple imputation and provide commands to easily extract and analyze the imputed data. Although fairly robust and frequently recommended, however, multiple imputation is never ideal, particularly in real-world datasets in which missingness mechanisms can be hard to identify. Any data imputation practices are considered in light of the many other issues discussed previously -- how much data is missing, whether it is MCAR/MAR/MNAR, how central the missing data is to the analysis, etc. Even best statistical practices may not be enough to redeem datasets plagued by skipped items.

Method

Participants

Approximately 2300 engineering graduate students from a nationally representative sample were contacted for participation, with 1754 (76%) completing the survey. For this paper, responses to items asking about identity-based motivation were treated as an independent dataset and tested for unit and item nonresponse.

Measures

Survey items were developed from scales originally used with undergraduate students, with the items modified based on feedback from qualitative interview sessions and factor analysis from pilot interviews.[13] Participants were asked to respond to 27 items asking about their identities, and 2 items asking about their degree progress and intentions to persist, all on 1-5 Likert scales (see Appendix 4 for the item text). The 27 identity items were those being checked for significant missingness, and the 2 experience items were used as potential predictors.

Analysis & Results

Since the framework for the analysis is provided previously, we will present the analyses conducted for this paper and their results together. Of the dataset selected above, 19 participants left all survey responses blank (e.g., unit nonresponse). These cases were dropped, and the number of skipped items (624) were calculated as a percentage of the total items presented (46,845; 1.33%). A correlation matrix was created to search for relationships in missingness, e.g., if participants who skipped item 1 also tended to skip item 2 (see Figure 3 for and Table 1 in Appendix 5 for values). An aggregation plot was also to explore patterns in missingness (Appendix 5, Figure 4); the bar plot on the left shows the number of missing responses for each item, and the plot on the right shows the different combinations of skipped items.

Overall, these results do not indicate serious issues with missingness, but for demonstration purposes we continued with the analysis. Little's MCAR was not significant, indicating that data is missing completely at random, $\chi^2 = 638.14$, $p = 0.894$. Again, to illustrate the procedure we continued analyses. Logistic regressions were used to see if the experience items predicted completion of the identity items; specifically, to see if students who struggled to evaluate their degree progress or had lower intentions to persist were more likely to skip items. Fifty-four logistic regressions were run, with each item acting as a dependent variable and the predictors tested alone. Missingness in item 8 did was significantly related to difficulty in evaluating degree progress, $\beta = -.74$, $OR = .47$, $p = .014$. In other words, a 1-point increase in difficulty evaluating degree progress increases the chance of a skipped response by 47%. As earlier tests did not prove significant results, this relationship is likely spurious, but it does demonstrate how results are displayed in the code.

If results were more significant overall, indicating serious issues in missingness, we would look at the patterns to try and explain why some items were skipped, how often, and by who. For instance, if Little's MCAR was significant and difficulty in evaluating degree progress predicted missingness in items 4-15, we might theorize a third-variable explanation (e.g., students who have not done much research struggle to evaluate their progress and are skipping items that don't apply to them). As a separate question asks about the number of publications and presentations participants have done, we could look at the relationship between items, scores, and missingness patterns. This would suggest that data are MNAR, and that some form of data imputation should be used and/or inferential results should be interpreted with extreme caution.

Discussion

In conclusion, the process of assessing missingness is often time-consuming and involved, with an often frustrating lack of clarity in rules and procedures. Most importantly, however, for large surveys like the GRADs project, missingness is not assessed only once. Described here are results of missingness analysis for 27 identity-based motivation questions, only an estimated 18% of the approximately 150 items participants were asked to complete. As a result, it's necessary to continue checking for missingness when running new analyses, no matter how many times the dataset has been used. The most ideal finding is that data are missing completely at random, or even better, not missing significantly at all, although goalposts as to 'significant' missingness are not well established. Unlike many forms of inferential analysis, missingness analysis does not have clear cut-offs that aid in differentiating between random noise and problematic patterns; ultimately, it is up to the researcher to do their due diligence and argue for the generalizability of their data.

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Heather Perkins is a graduate student studying at North Carolina State University in the Applied Social and Community Psychology program. She entered the program in the fall of 2014, after completing her Bachelor of Science in Psychology from the University of Cincinnati. Her primary research interest is identity and identity processes, as well as the teaching of psychology and research methods.

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Dr. Cheryl Cass is a Teaching Associate Professor in the Department of Materials Science and Engineering at North Carolina State University (NCSU) where she has served as the Director of Undergraduate Programs since 2011. She earned a B.S. degree in biomedical engineering from NCSU and M.S. and Ph.D. degrees in bioengineering from Clemson University, where she also served as a postdoctoral researcher in the Department of Engineering and Science Education. Her current research focuses on the intersection of science and engineering identity in post-secondary and graduate level programs.

Appendix 1

R Code Sample

For ease of access, the R code is provided online here.

Appendix 2

Figure 1A-1G

For more information on what is represented in each graph, see page 2 of the manuscript.

Figure 1A

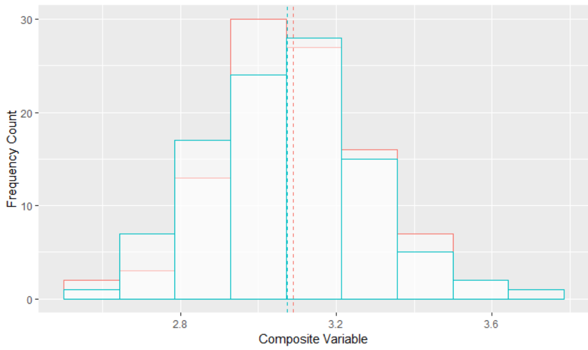


Figure 1B

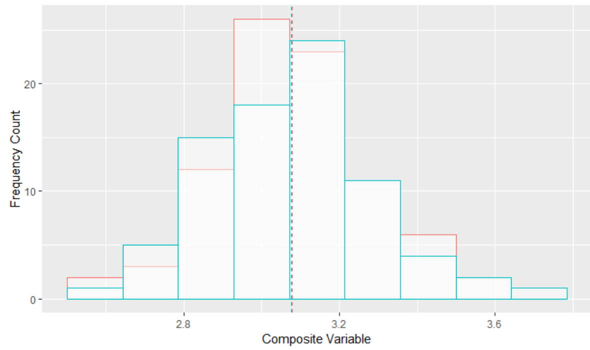


Figure 1C

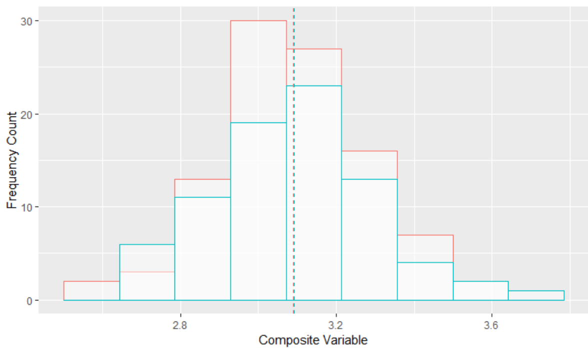


Figure 1D

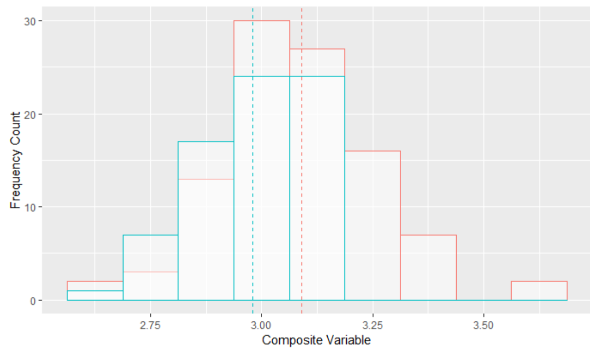


Figure 1E

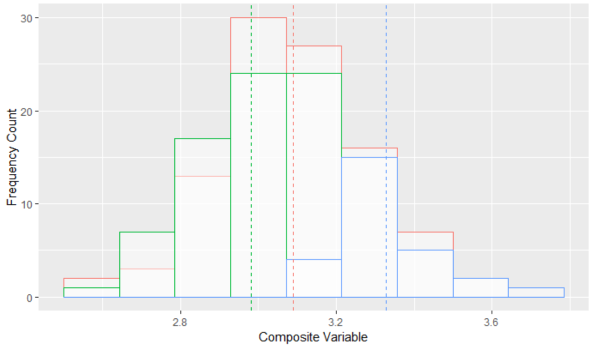


Figure 1F

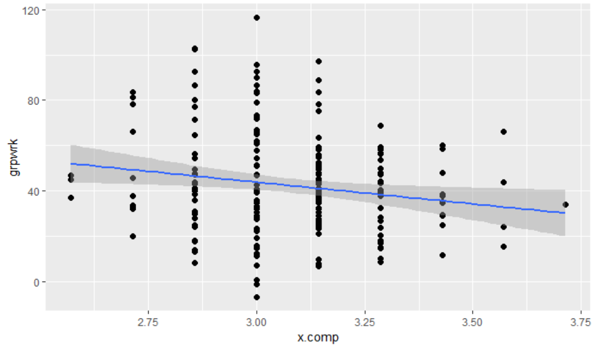
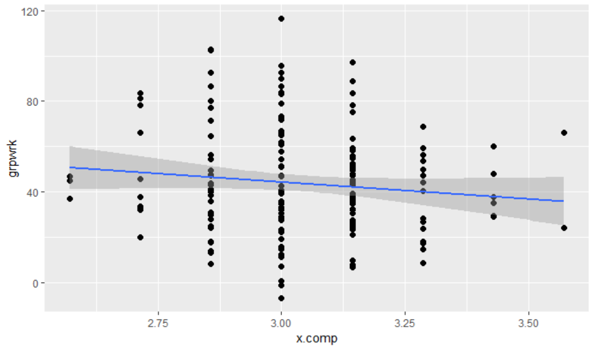


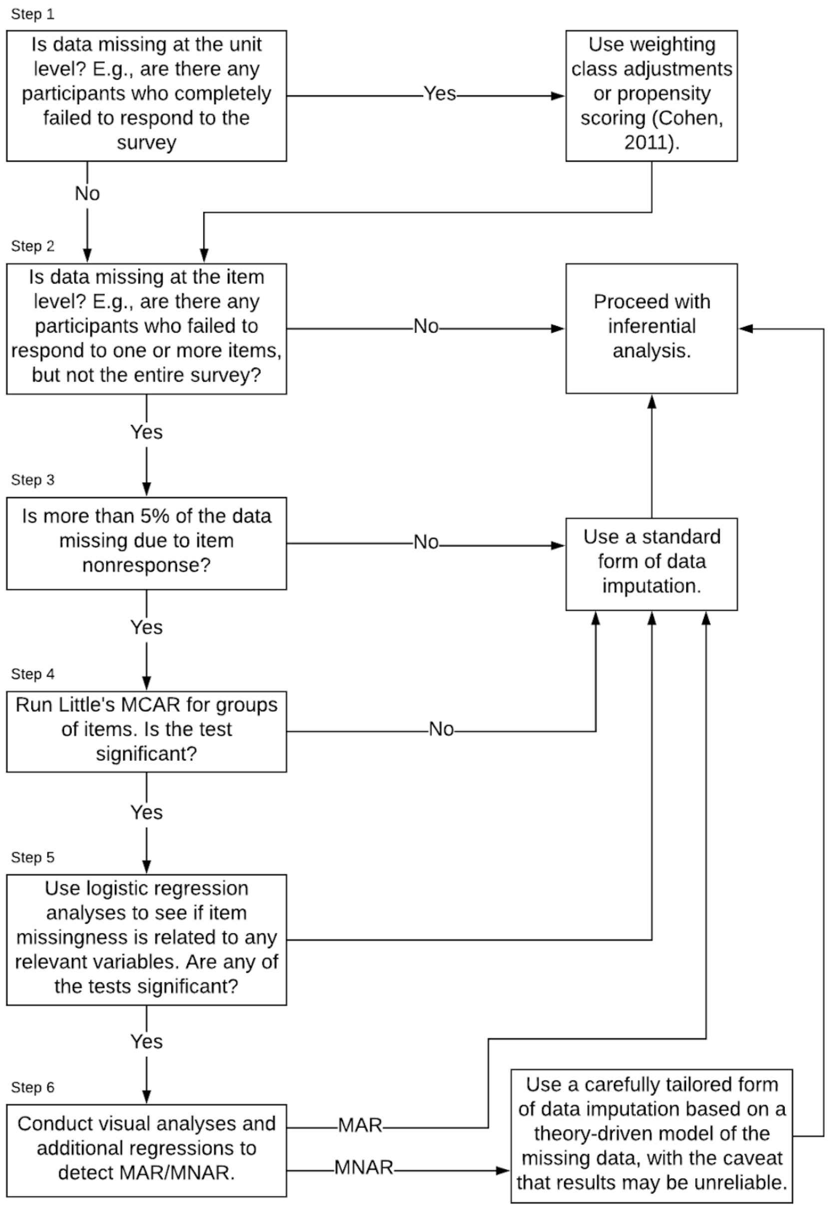
Figure 1G



Appendix 3

Figure 2

Flowchart illustrating the process of analyzing missing data.



Appendix 4
Item text from survey. All survey items on a Likert scale, 1 = "Strongly disagree", 5 = "Strongly agree".

1. When I read journal articles, I feel like a/an…scientist
2. When I read journal articles, I feel like a/an…engineer
3. When I read journal articles, I feel like a/an…researcher
4. When I write peer-reviewed papers, I feel like a/an…scientist
5. When I write peer-reviewed papers, I feel like a/an…engineer
6. When I write peer-reviewed papers, I feel like a/an…researcher
7. When I conduct research, I feel like a/an…scientist
8. When I conduct research, I feel like a/an…engineer
9. When I conduct research, I feel like a/an…researcher
10. When I attend conferences, I feel like a/an…scientist
11. When I attend conferences, I feel like a/an…engineer
12. When I attend conferences, I feel like a/an…researcher
13. When I present my results, I feel like a/an…scientist
14. When I present my results, I feel like a/an…engineer
15. When I present my results, I feel like a/an…researcher
16. When I attend classes, I feel like a/an…scientist
17. When I attend classes, I feel like a/an…engineer
18. When I attend classes, I feel like a/an…researcher
19. When I do homework, I feel like a/an…scientist
20. When I do homework, I feel like a/an…engineer
21. When I do homework, I feel like a/an…researcher
22. When I collaborate with other graduate students, I feel like a/an…scientist
23. When I collaborate with other graduate students, I feel like a/an…engineer
24. When I collaborate with other graduate students, I feel like a/an…researcher
25. Overall, I see myself as a/an…scientist
26. Overall, I see myself as a/an…engineer
27. Overall, I see myself as a/an…researcher
28. I find it difficult to evaluate my degree progress
29. I intend to complete my graduate degree

Appendix 5

Figure 3

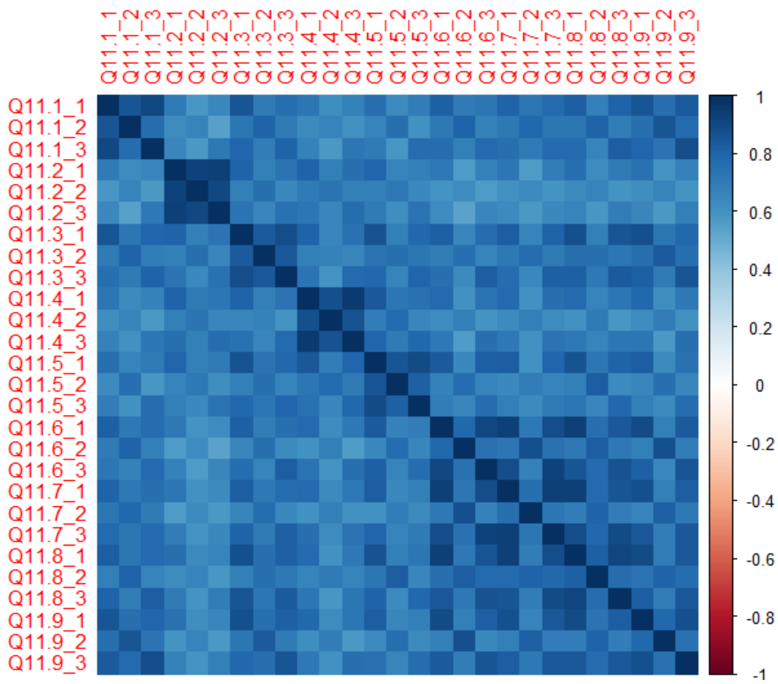


Figure 4

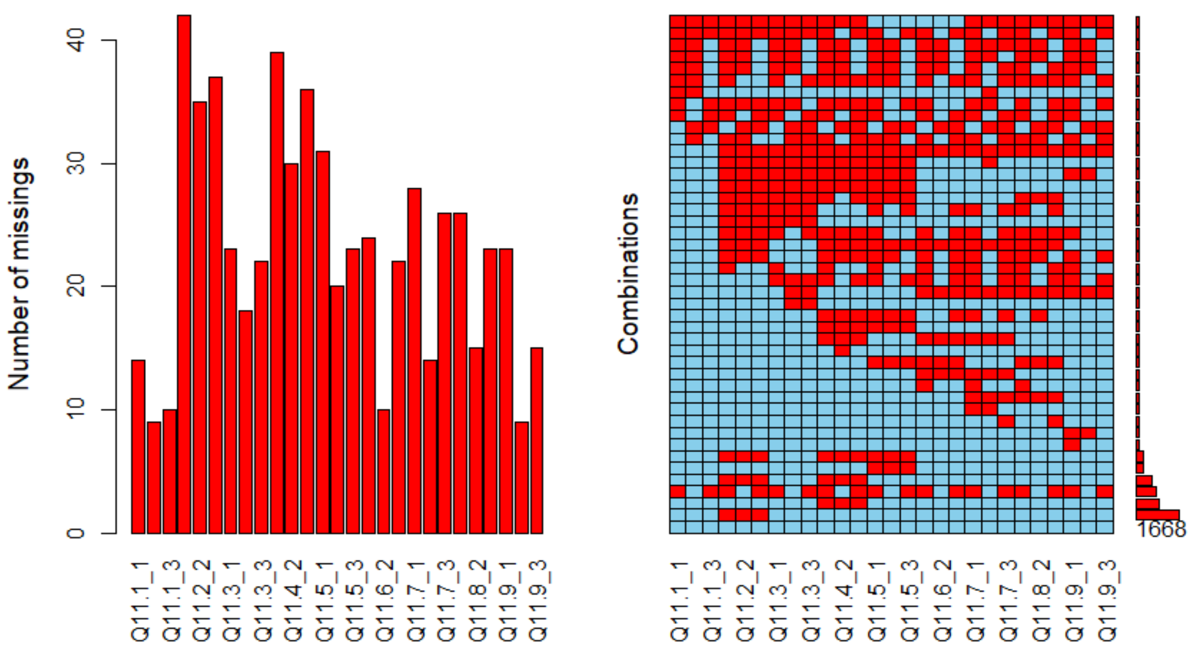


Table 1

Table of correlation matrix indicating missingness patterns. Values on the top diagonal are correlation coefficients, values on the bottom diagonal are p-values.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1		0.85	0.90	0.71	0.58	0.64	0.86	0.71	0.76	0.73	0.61	0.67	0.76	0.63	0.69	0.82	0.71	0.73	0.81	0.72	0.77	0.83	0.68	0.80	0.86	0.75	0.83
2	0.00		0.77	0.62	0.66	0.55	0.72	0.80	0.70	0.64	0.67	0.60	0.66	0.75	0.60	0.72	0.80	0.67	0.71	0.79	0.73	0.73	0.81	0.69	0.75	0.85	0.77
3	0.00	0.00		0.66	0.57	0.71	0.80	0.70	0.81	0.68	0.57	0.72	0.70	0.59	0.77	0.76	0.68	0.78	0.75	0.71	0.77	0.77	0.66	0.83	0.80	0.73	0.89
4	0.00	0.00	0.00		0.92	0.94	0.80	0.69	0.73	0.80	0.69	0.75	0.79	0.67	0.68	0.71	0.56	0.67	0.72	0.57	0.70	0.76	0.63	0.70	0.74	0.60	0.67
5	0.00	0.00	0.00	0.00		0.91	0.68	0.75	0.65	0.71	0.73	0.69	0.68	0.71	0.64	0.59	0.62	0.56	0.60	0.63	0.60	0.64	0.67	0.60	0.62	0.66	0.60
6	0.00	0.00	0.00	0.00	0.00		0.74	0.65	0.74	0.73	0.66	0.77	0.71	0.61	0.74	0.62	0.54	0.66	0.63	0.57	0.65	0.67	0.59	0.69	0.65	0.57	0.68
7	0.00	0.00	0.00	0.00	0.00	0.00		0.83	0.89	0.81	0.65	0.74	0.87	0.68	0.78	0.82	0.65	0.77	0.83	0.66	0.80	0.87	0.68	0.85	0.88	0.72	0.79
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.84	0.68	0.67	0.66	0.74	0.76	0.73	0.70	0.76	0.66	0.71	0.77	0.70	0.75	0.76	0.73	0.76	0.84	0.76
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.73	0.59	0.77	0.79	0.67	0.79	0.76	0.63	0.83	0.77	0.65	0.81	0.81	0.72	0.84	0.81	0.70	0.85
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.88	0.95	0.85	0.73	0.74	0.77	0.60	0.73	0.78	0.61	0.76	0.78	0.67	0.72	0.78	0.61	0.71
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.86	0.70	0.77	0.65	0.62	0.68	0.59	0.64	0.69	0.63	0.61	0.70	0.58	0.63	0.70	0.60
12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.79	0.71	0.78	0.71	0.57	0.75	0.72	0.60	0.74	0.72	0.66	0.72	0.72	0.58	0.76
13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.86	0.89	0.84	0.65	0.81	0.82	0.61	0.80	0.86	0.72	0.80	0.82	0.63	0.75
14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.81	0.68	0.77	0.67	0.65	0.69	0.66	0.68	0.82	0.63	0.66	0.75	0.65
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.70	0.65	0.77	0.69	0.64	0.71	0.73	0.65	0.78	0.68	0.63	0.76
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.79	0.90	0.93	0.71	0.88	0.93	0.75	0.84	0.89	0.69	0.83
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.75	0.73	0.87	0.74	0.71	0.82	0.71	0.68	0.88	0.70
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.89	0.67	0.93	0.86	0.77	0.86	0.81	0.64	0.85
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.76	0.93	0.93	0.77	0.85	0.87	0.68	0.82
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.72	0.69	0.80	0.69	0.66	0.82	0.71
21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.89	0.79	0.89	0.85	0.70	0.84
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.81	0.92	0.89	0.70	0.84
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.76	0.74	0.81	0.76
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.83	0.69	0.84
25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.78	0.87
26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.74
27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	