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ABSTRACT

The effectiveness of four methods of handling missing data in reproducing the target sample covariance matrix and mean vector was tested using three levels of incomplete cases: 30%, 50%, and 70%. Data were selected from the National Education Longitudinal Study (NELS) database. Three levels of sample sizes (500, 1000, and 2000) were used. The assumption of missing data completely at random was violated in all samples. Results indicate that listless deletion was most effective in replicating the target mean vector and covariance matrix. (Contains 2 tables, 1 figure, and 19 references.) (Author/SLD)

Running Head: Missing Data Method

Effectiveness of Four Methods of Handling Missing Data Using Samples from a National Database

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Paper presented at the Annual Conference of the American Educational Research Association, New Orleans, April 24-28, 2000.

Abstract

The effectiveness of four methods of handling missing data in reproducing the target sample covariance matrix and mean vector was tested using three levels of incomplete cases: 30%, 50%, and 70%. Data was selected from the NELS (National Educational Longitudinal Study) database. Three levels of sample size (500, 1000, 2000) were used. The assumption of missing completely at random was violated in all samples. Results indicate listwise deletion was most effective in replicating the target mean vector and covariance matrix.

Effectiveness of Four Methods of Handling Missing Data Using Samples from a National Database

When data is analyzed in survey research, often there are missing values. If the mechanism causing the missing values is known, the solution to this problem may be incorporated in the study. Inevitably, however, when data are collected by survey, subjects may fail to answer some questions for reasons unknown to the researcher. Ignoring this problem may lead to analysis of data that is of dubious value.

In addition, different methods of handling missing values may produce different results. When Jackson (1968) entered data on all the available variables in a discriminant analysis, the significance of the regression coefficients of individual variables, as well as the interpretation of the importance of these variables, changed with the missing value method used. Witta and Kaiser (1991) also reported that the regression coefficients and total variance accounted for by the variables changed depending on the method used to handle missing values. After re-analyzing three studies of private/public school achievement, Ward and Clark III (1991) concluded that the method used to handle missing data influenced the outcome of these studies.

In using the National Educational Longitudinal Study of 1988 database to investigate the effects of part-time work on school outcomes Singh and Ozturk (1999) eliminated more than half of the selected cases by listwise deletion of the incomplete data. Which leads to the question, was listwise deletion an appropriate method of for handling the missing data or, would another method be more effective?

Statement of the Problem

The purpose of the current study was to investigate the effectiveness of four methods of handling missing data using the 26 variables in the Singh and Ozturk study. Effectiveness was defined as the probability of accurately reproducing the true covariance matrix and mean vector. Effectiveness of the missing data methods was assessed by manipulating the proportion of cases containing missing values and the sample size. The missing data methods studied were listwise deletion, pairwise deletion, regression and expectation maximization. Sample sizes investigated were 500, 1000, and 2000. The proportion of incomplete cases in each sample were 30%, 50%, and 70%.

Until recently, the only methods available with popular statistical computer software focused on handling the missing data problem by deleting subjects with incomplete information, deleting the missing values, or replacing the missing value with some reasonable estimate. Now, however, new subroutines are available to provide more assistance in handling missing data and providing analysis choices using iterative regression or expectation maximization (EM) procedures. These relative new methods (in current software) also provide the possibility of specifying the model to be used (i.e., multivariate normality, adding a randomly selected error).

Methods Studied

Listwise Deletion

Listwise deletion is probably the most frequently used method of handling missing data and is available as a default option in several statistical software programs including. This method discards cases with a missing value on any variable and thus is very wasteful of data. Listwise deletion, however, has been shown to be effective with low average intercorrelation, less than

four variables and a small proportion of missing values (Chan, et.al., 1976; Haitovsky, 1968; Timm, 1970). The assumption of missing completely at random is crucial to the use of this method. It is more likely, however, to find the complete sample different in important ways from the incomplete sample (Little & Rubin, 1987). Problems for a researcher using this method include a reduction in power and an increase in standard error due to reduced sample size and the possible elimination of sub-populations.

Pairwise Deletion

When using pairwise deletion, covariances are computed between all pairs of variables having both observations, eliminating those that have a missing value for one of the two variables (Glasser, 1964). Means and variances are computed on all available observations. The assumption made is that the use of the maximum number of pairs and all the individual observations yield more valid estimates of the relationship between the variables. It is assumed that when two variables are correlated, information on one improves the estimates of the other variable. It is also assumed that the pairs are a random subset of the sample pairs. If these assumptions are true, pairwise deletion produces unbiased estimates of the variable means and variances (Hertel, 1976). When missing data are not missing completely at random, however, the correlation matrix produced by pairwise deletion may not be Gramian (Norusis, 1988b).

Marsh (1998) investigated the estimates produced when using pairwise deletion for randomly missing data. From this study, which included five levels of missing data and three sample sizes, Marsh concluded parameter variability was explained, parameter estimates were unbiased, and only one covariance matrix was nonpositive definite.

Regression

Regression as an imputation method has many variations. The regression methods rely on information contained in non-missing values of other variables to provide estimates of missing values. As the average intercorrelation and the number of variables from which these methods can obtain information increases, the regression methods, theoretically, perform better. Too many variables, however, can cause problems with over prediction (Kaiser & Tracy, 1988) and too high an average intercorrelation can result in a singular matrix. In these cases, regression does not perform well.

Variations in the regression methods include differences in methods of developing the initial correlation matrix (listwise deletion, pairwise deletion, and mean substitution) and the presence or absence of iteration procedures. Differences in regression methods also include the use of randomly selected residuals for iterations and assumptions of a normal distribution. Theoretically, the more variables considered that provide additional information, the better the estimate. Mundfrom and Whitcomb (1998) investigated the effects of using mean substitution, hot-deck imputation, and regression imputation on classification of cardiac patients. Mean substitution and hot-deck imputation correctly classified patients more frequently than regression imputation.

Expectation Maximization

Dempster, Laird, and Rubin (1977) recommended the use of the EM algorithm which imputes estimates simultaneously in an iterative procedure. The E step of this algorithm finds the conditional expectation of the missing values. The M step performs maximum likelihood estimation as if there were no missing data. The primary difference between this procedure and the regression procedure is that the values for the missing data are not imputed and then iterated.

The missing values are functions based on the conditional expectation (Little & Rubin, 1987).

This method of handling missing data represents a fundamental shift in the way of thinking about missing data (Schafer & Olsen, 1998).

Pattern of Missing Values

All of the missing data handling procedures discussed require data missing at random (MAR) or missing completely at random (MCAR). Yet Cohen and Cohen (1983) suggested that in survey research the absence of data on one variable may be related to another variable and may be due to the value of the variable itself. When investigating simultaneously missing values, Witta (1996/97) found concurrently missing values ($p<.001$) in three of four samples using data from a national database.

Schafer and Olsen (1998), however, argue convincingly that "every missing-data method must make some largely untestable statistical assumptions about the manner in which the missing values were lost" (p551). Consequently, when analyzing real data, researchers typically assume missing at random.

Procedure

All high school seniors who had reported working during their senior year of high school and for whom base-year and first follow-up data were available were included in this study. The initial sample contained the 26 variables used in the Singh and Ozturk study for 4664 subjects. These subjects were split into three populations: those containing one or more missing values but less than 14 (n=1542), those containing more than 13 missing values (n=19), and those containing no missing values on any variable (n=3103). The 19 subjects having missing values for more than half the variables were eliminated from further analysis. The remaining two populations (n=4645)

were used to create samples for analysis.

Creating Test Samples

A sample consisting of 2000 cases was randomly selected from the non-missing population. This sample was duplicated twice resulting in three identical samples of 2000 cases containing no missing values. These samples were used to provide estimates of the target (true) covariance matrices and mean vectors.

A sample of 1400 cases was randomly select from the missing population. These cases were used to replace an equal number of randomly selected cases from one of the target samples. This provided a test sample of 2000 with 70% of the cases containing missing values. It was assumed that the replacement incomplete cases were similar to the complete cases that were removed. This process was repeated with the second target sample to provide a test sample with 50% (1000) of the cases containing missing values. The process was repeated again with the third target sample to provide a test sample with 30% (600) of the cases containing missing values.

This entire procedure was repeated twice to provide test samples with 30%, 50%, and 70% of the cases containing missing values in test samples of 1000 and 500 cases. Thus, 9 test samples were created.

Analysis

Covariance matrices and mean vectors for the missing data handling methods were produced by the missing data subroutine in SPSS. The test for missing completely at random and pattern of missing data was also produced by this subroutine. The variable means produced by each method were compared with the corresponding mean values of the target sample using the MANOVA (multivariate analysis of variance) subroutine in SPSS for every method except

pairwise deletion.

Because the MANOVA subroutine does not accept pairwise deletion, the vector of variable means produced by pairwise deletion was compared to that of the target sample using Quattro Pro. The mean vector tested for pairwise deletion was the mean given for all values of each variable. Multi-sample analysis in LISREL (Joreskog & Sorbom, 1989, chap. 9) was used to test the equality of the covariance matrices produced by various missing data handling methods to the covariance matrix of the target sample.

Results

Randomness of Missing Values

When variables from the total sample were tested for no difference in variable based upon missingness of another variable, results suggested the missing data may not be missing at random and is not missing completely at random. For example, cases not missing a standardized test ($n \geq 3344$) had average reported grades ranging from 6.4 to 7.2 (high=low grade). The average reported grades for cases missing a standardized test ($n \geq 698$) ranged from 7.0 to 7.5. The average grade reported for a given missing standardized test was always at least 0.2 points higher (lower grade) than the non-missing equivalent.

In addition, none of the nine samples used in the current study contained data missing completely at random. The frequency of simultaneously missing variables for each sample is depicted in Figure 1. The category of 'Std Test' consists of four simultaneously missing standardized test variables (History, Math, Reading, and Science). The standardized test variables were also missing in conjunction with missing values for grades which is depicted in Figure 1 as 'Grd & Test'. The four grade variables were also missing simultaneously. If a variable did not

contain a missing value for 10% of the sample cases, it was included in the 'Other' category. In each sample, the majority of the cases containing missing values consisted of concurrently missing values for standardized tests (the categories 'Std Test' and 'Grd & Test').

Insert Figure 1 About Here

Covariance Matrix Reproduction

Surprisingly, all four missing data methods adequately reproduced (χ^2 $p>.05$) the target sample covariance matrix when 30% or 50% of the cases contained missing values regardless of sample size[1]. In addition, as depicted in Table 1, the goodness of fit index in all cases was above 0.98 and the root mean square residual was less than 1 except for two cases.

When 70% of the cases contained missing values, however, only the covariance matrix produced by the EM algorithm passably reproduced the target sample matrix when the sample size was 500. When the sample size was 1000 or 2000 with 70% of the cases containing missing values, no method adequately reproduced the target sample covariance matrix as measured by chi-square (χ^2, $p<.05$). The goodness of fit index for these conditions remained at an acceptable level of 0.96 or higher. The root mean square residual also remained relatively small as shown in Table 1.

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[1]To prevent discrepancies in sample size comparison, the n for testing the covariance matrices produced by Listwise and Pairwise deletion was enter in LISREL as the target n (i.e. if the target sample contained 500 cases, the n entered for the listwise deletion covariance matrix was 500).

Insert Table 1 About Here

Mean Vector Tests

When 30% of the cases contained missing values, all missing data methods adequately reproduced the target sample mean vector as measured by F ($p<.05$) regardless of sample size[2] as depicted in Table 2. In addition, less than 2% of the difference in mean vectors could be explained by missing data method group as measured by eta square.

When 50% of the cases contained missing values and the sample size was 500, all missing data methods adequately reproduced the target sample mean vector again. However, the variance accounted for by missing data method had increased to approximately 3% when the target sample mean vector was contrasted to the vector produced by the EM algorithm or the vector produced by regression. When the sample size increased to 1000, all methods except the EM algorithm adequately reproduced the target sample mean vector ($p<.05$). The variance accounted for by missing data method was again 2% or less. When the sample size increased to 2000, only listwise deletion adequately reproduced the target sample mean vector. The variance in mean vectors accounted for by group was again 2% or less.

When the proportion of cases containing missing values increased to 70%, only listwise deletion adequately reproduced the target sample mean vector in all conditions. When the sample

[2]Because sample size varies by variable when pairwise deletion is used, the pairwise deletion n was set to the n of listwise deletion for all calculations.

size was 500 or 1000, neither the EM algorithm nor the regression procedure effectively reproduced the target mean vector (p <.01). When the sample size increased to 2000, only listwise deletion was effective. In addition, the variance in mean vectors accounted for by group differences had increased to 5% in some instances as presented in Table 2.

Insert Table 2 About Here

Discussion and Conclusions

When 30% of the cases in a sample were incomplete, all missing data methods tested adequately reproduced the target sample covariance matrix and mean vector regardless of sample size. This would imply that if only a few cases were incomplete in a sample, the choice of method used to handle missing data could be made based upon considerations of loss of data (in the deletion methods) or other substantive reasons. When, however, 50% of the cases were incomplete, only listwise and pairwise deletion were effective under all conditions. While this could be attributed to reduction in sample size, only 1% of the variance between mean vectors could be explained by the listwise deletion method, 1-2% by pairwise deletion, and 2-3% by the other methods. This finding suggests that listwise deletion would be the method of choice regardless of reduction in sample size.

Although no method adequately reproduced the target sample covariance matrix when 70% of the cases were incomplete as measured by χ^2, the goodness of fit index was adequate for all methods. The root mean square residual results indicated an adequate fit for the listwise deletion and regression methods and a tolerable fit for pairwise deletion and the EM algorithm.

Listwise deletion, however, consistently reproduced the mean vector across all conditions. Thus, this finding would also suggest that listwise deletion would be the method of choice.

This study was limited to one sample size and proportion of incomplete cases for each test. Consequently, results may be specific to these samples. In addition, it was assumed the replacement incomplete cases were similar to the complete cases they replaced. If this assumption was not valid, these results may change with the next sample. These limitations, however, did not influence the pattern of missing values. In all instances the missing data were not missing completely at random. Because there is no specific test for missing at random (Hill, 1997), no conclusion concerning it can be made. However, examination of the data provided suggests that this assumption is also violated.

The most prevalent missingness pattern existed in the concurrently missing values for standardized tests and grades. This pattern may explain why listwise deletion fared better than other methods. If the most highly related variables (standardized test scores) contain concurrently missing values, any method relying on other variables to estimate a variable suffers. If, in addition, these concurrently missing values are also missing simultaneously with another variable (grades) that should be related, the situation becomes even worse. Thus, an assumption for use of each missing data method test was violated in each sample.

The most surprising result of this study was the relatively effective performance of each missing data method when considering the violation of the missing completely at random and missing at random assumptions. The failure to satisfy the randomness assumption, however, is the primary finding of importance in this study. This finding suggests that other samples selected from the NELS database would also contain non-randomly missing values. In light of this finding it

would be suggested that future missing data research focus on methods to overcome the randomness limitation. Researchers in all areas are cautioned to examine the data prior to any analysis. Before making any decisions concerning method of handling missing data, the pattern of missingness must be scrutinized.

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Tables & Figures

Table 1

Test of Missing Data Method Covariance Matrix to Target Matrix

	N=500			N = 1000			N = 2000		
Method	χ^2	GFI	RMR	χ^2	GFI	RMR	χ^2	GFI	RMR
30%									
Listwise	95.18	.993	.17	90.08	.997	.15	79.39	.998	.10
Pairwise	137.97	.990	.27	116.34	.996	.31	171.11	.997	.38
EM	137.48	.990	.26	113.09	.996	.31	165.22	.997	.38
Regression	93.53	.993	.17	91.07	.997	.15	83.08	.998	.10
50%									
Listwise	183.72	.986	.59	212.15	.992	.15	195.09	.996	.24
Pairwise	224.31	.984	1.30	285.15	.996	.85	285.69	.995	.51
EM	220.60	.984	1.48	272.05	.990	.93	276.72	.995	.59
Regression	183.86	.986	.59	212.13	.992	.15	200.69	.996	.24
70%									
Listwise	414.50*	.967	.47	493.01**	.981	.56	459.51**	.991	.40
Pairwise	426.61**	.971	1.27	438.93**	.985	.85	540.11**	.991	1.19
EM	393.02	.973	1.20	427.83**	.985	.99	524.50**	.991	1.23
Regression	417.12**	.967	.47	500.98**	.980	.56	462.03**	.991	.40

Note. df=351. *$p \leq .05$. **$p \leq .01$.

Table 2

Contrast of Missing Data Method Mean Vector with Target Mean Vector

	N = 500			N = 1000			N = 2000		
	F	df	η^2	F	df	η^2	F	df	η^2
30%									
Listwise	.095	823	<.01	.179	1673	<.01	.163	3373	<.01
Pairwise	.303	823	<.01	.514	1673	<.01	.768	3373	<.01
EM	.459	973	.01	.783	1973	.01	1.19	3973	<.01
Regression	.509	973	.01	.897	1973	.01	1.12	3972	<.01
Group	.321	5445	<.01	.505	10978	<.01	.751	22039	<.01
50%									
Listwise	.296	723	.01	.353	1473	<.01	.402	2973	<.01
Pairwise	.515	723	.02	.738	1473	<.01	1.49	2973	.01
EM	1.00	973	.03	1.61*	1973	.02	3.44**	3973	.02
Regression	1.13	972	.03	1.47	1971	.02	3.14**	3969	.02
Group	.664	5143	.01	1.01	10379	<.01	2.00**	20833	<.01
70%									
Listwise	.484	623	.02	.456	1273	<.01	.550	2573	<.01
Pairwise	.569	623	.02	1.025	1273	.01	4.49**	2573	.03
EM	1.97**	973	.05	3.36**	1973	.04	7.09**	3973	.04
Regression	1.86**	971	.05	3.41**	1971	.04	6.54**	3969	.04
Group	1.23	4842	.02	1.92**	9778	.02	3.50**	19637	.04

Note. Group test does not include pairwise deletion. $^*p \le .05$. $^{**}p \le .01$.

Figure 1

Patterns of Missing Values

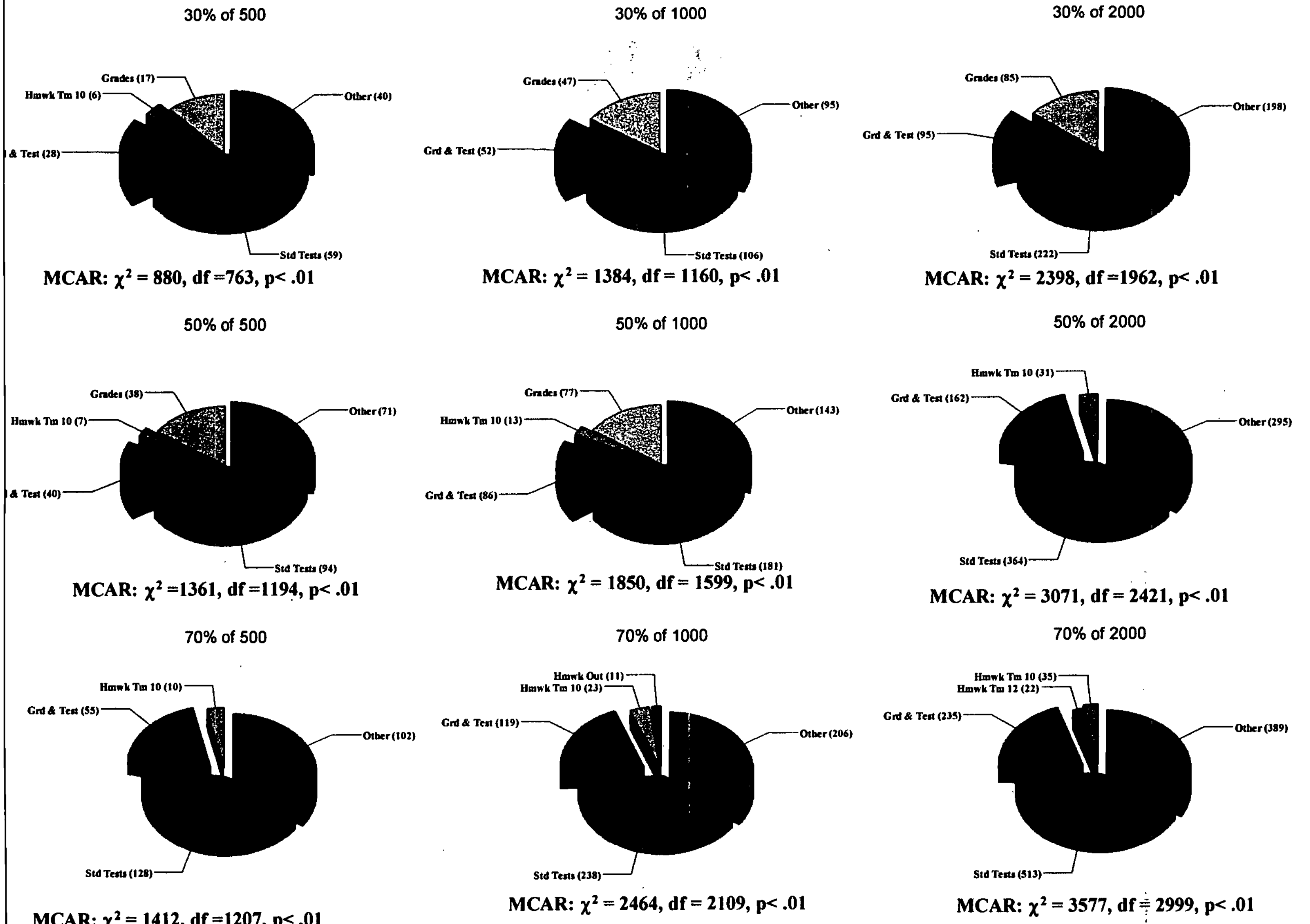

Figure 1

Patterns of Missing Values

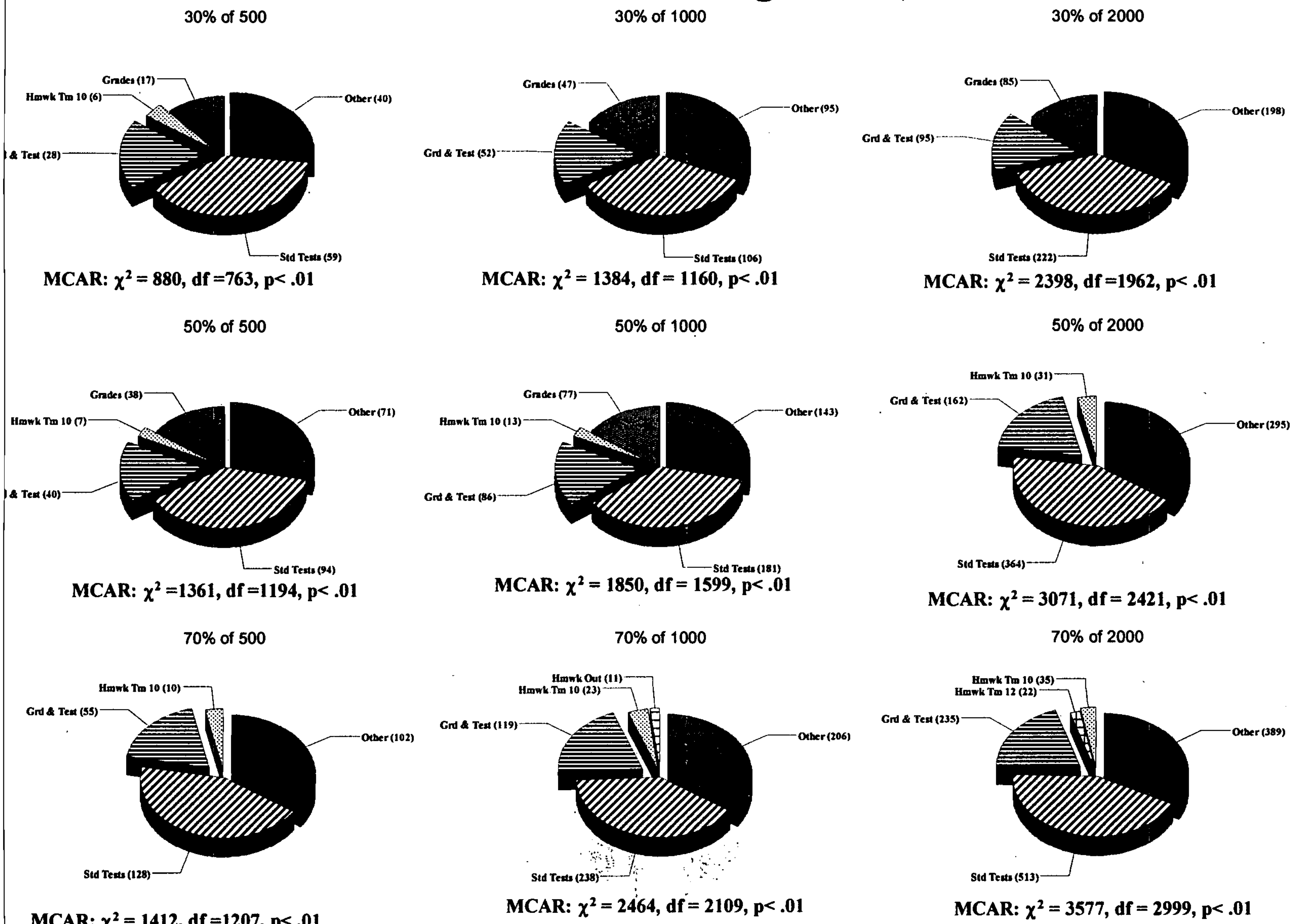

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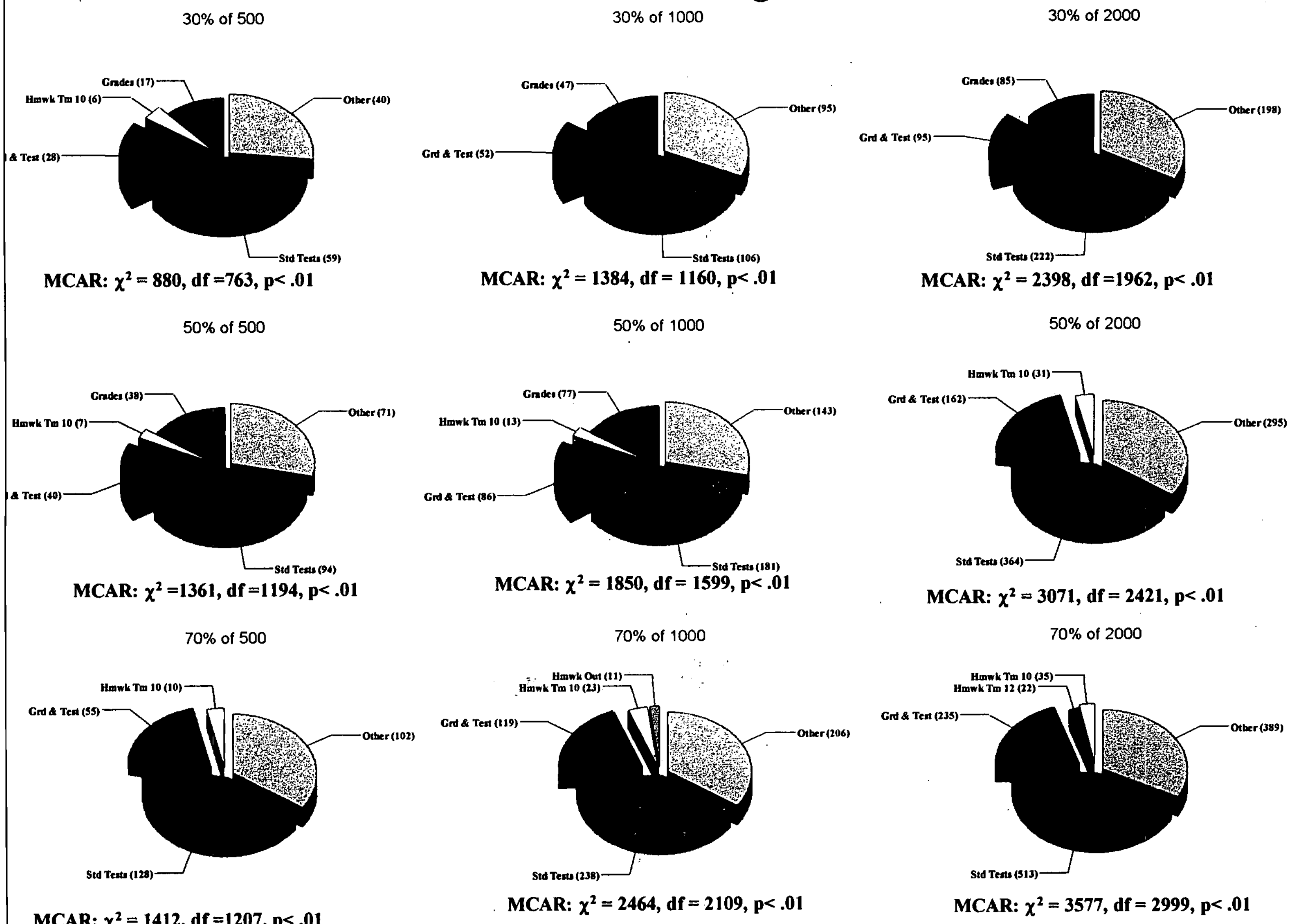
Figure 1

Patterns of Missing Values



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