

Missing Data Workshop
 Joint Doctoral Program in Clinical Psyc



Missing Data Workshop

Jonathan Lee Helm
 Friday May 17th, 2019

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Grand Overview

- Introduction to missing data
- Review of sampling
- Patterns, causes, and mechanisms of missing data
- The problem with missing data

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Introduction to Missing Data

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Missing Data

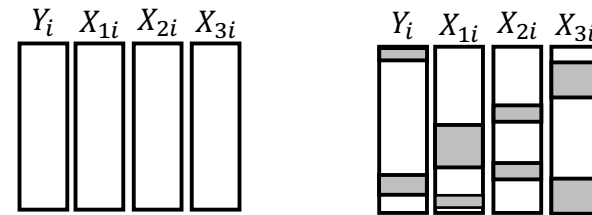
- Missing data occur when we do not have one or more observations for a given variable in our data

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Missing Data

- Missing data occur when we do not have one or more observations for a given variable in our data



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Missing Data

- Missing data are ubiquitous in psychological science
- Can anyone think of a real world example that has complete data in psychological science?

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Missing Data

- Missing data pose potential problems

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Missing Data

- Missing data pose potential problems
- Potential for biased estimates
- Potentially increase standard errors
 - Smaller sample size
 - Higher Type 2 error rate (i.e., harder to detect sig. effects)

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Missing Data

- Missing data pose potential problems
- Potential for biased estimates
- Potentially increase standard errors
 - Smaller sample size
 - Higher Type 2 error rate (i.e., harder to detect sig. effects)
- These potential problems can be mitigated by different analyses
 - Multiple imputation

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Missing Data

- The reasons that missing data may cause problems are closely linked to the importance of random sampling
- Let's review random sampling as a segue into missing data

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Grand Overview

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Review of Sampling

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Sampling

- The problems associated with missing data can be conceptualized in terms of sampling

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Sampling

- Scientific process:
 1. Random sample
 2. Measure
 3. Analyze
 4. Draw conclusions

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Sampling

- Scientific process:
 1. Random sample
 2. Measure
 3. Analyze
 4. Draw conclusions

This is an important feature!
Random sampling implies
generalizability

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Sampling

Population

Sample

Random Sample

- All members of pop. have equal chance of being selected
- The results from the analysis should generalize to the population

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Sampling

- Example of a random sample
- And a random sample of a random sample

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

➔

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

➔

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

The sample mean for JS = 10.3
The sample SD for JS = 2.8

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

➔

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

The sample mean for JS = 10.3
The sample SD for JS = 2.8

Generalizability is a function of sampling

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

➔

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample mean for JS = 10.3
Sample SD for JS = 2.8

➔

Random Sample of Random Sample

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	118
50	14	134

Sample mean for JS = 10.2
Sample SD for JS = 3.1

Generalizability is a function of sampling

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Sampling

- Example of a non-random sample
- And a non-random sample of a random sample

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	4	80
100	6	73

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	4	80
100	6	73

Sample mean for JS = 7.1
Sample SD for JS = 1.1

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

Generalizability does not hold!

Non Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	4	80
100	6	73

Sample mean for JS = 7.1
Sample SD for JS = 1.1

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Pop. mean for JS = 10
Pop. SD for JS = 3

Generalizability is a function of sampling

Sample mean for JS = 10.3
Sample SD for JS = 2.8

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample mean for JS = 7.1
Sample SD for JS = 1.1

Non-Random Sample of Random Sample

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	80
50	14	73

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Sampling

- Missing data, in some cases can be conceptualized as a sample of a sample
- This occurs when we use listwise deletion
 - Delete any row that has a missing value

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample Remaining after Listwise Deletion

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	80
50	14	73

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample Remaining after Listwise Deletion

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	80
50	14	73

Listwise deletion will produce unbiased results if the remaining sample is still a random sample

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Sampling

- Take aways:
 - We have to perform sampling
 - Our results will generalize if we have a random sample
 - Missing data with listwise deletion can be conceptualized as a sample of a sample

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Grand Overview

- Introduction to missing data
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- The problem with missing data

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Patterns, Causes, and Mechanisms of Missing Data

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Patterns vs Causes vs Mechanisms

- Patterns of missingness
- Causes of missingness
- Missing data mechanisms
 - *Missing data assumptions*

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Patterns vs Causes vs Mechanisms

- Patterns of missingness
- Causes of missingness
- Missing data mechanisms
 - *Missing data assumptions*

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Patterns of Missingness

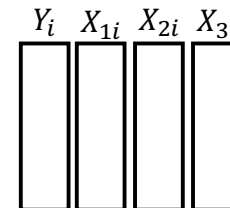
- A pattern of missingness is a pattern that occurs in a specific data set

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Patterns of Missingness

A pattern of missingness is a pattern that occurs in a specific data set



Complete data
No missingness
No missingness pattern

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Patterns of Missingness

A pattern of missingness is a pattern that occurs in a specific data set

Missing on X_{3i}
Univariate pattern

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Patterns of Missingness

A pattern of missingness is a pattern that occurs in a specific data set

Missing on more than one variable
General pattern

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Patterns of Missingness

In psychology, we usually have general patterns

We would like methods that can account for general patterns

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Patterns vs Causes vs Mechanisms

- Patterns of missingness
- Causes of missingness
- Missing data mechanisms
 - Missing data assumptions

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Cause of Missingness

- The ***true*** (not assumed) reason why the data are missing

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Cause of Missingness

- Example 1
- A researcher asks individuals to report their income
- Individuals with lower income tend to not report their income
- Cause of missingness: Those with lower income do not report their income

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Cause of Missingness

- Example 2
- A researcher performs an intervention on smoking
- Individuals that find the intervention challenging drop out
- There is missing data on smoking behavior at follow up
- Cause of missingness: Those that find the intervention to be challenging drop out

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Cause of Missingness

- Example 3
- A researcher performs an intervention on smoking
- Individuals that find the intervention challenging drop out
- There is missing data on smoking behavior at follow up
- Cause of missingness: Those that find the intervention to be challenging drop out

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Cause of Missingness

- Example 4
- A researcher performs measures intelligence longitudinally
- The researcher randomly assigns half of the sample to be measured at ages 5, and 7; and half at 6 and 8
- Cause of missingness: Planned missingness: The researcher creates the missingness by design

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Cause of Missingness

- The **true** (not assumed) reason why the data are missing
- Typically not known to the researcher
 - Counter: Planned missingness

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Patterns vs Causes vs Mechanisms

- Patterns of missingness
- Causes of missingness
- Missing data mechanisms
 - *Missing data assumptions*

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Missing Data Mechanisms

- A.K.A:
 1. Categories of missingness
 2. Types of missingness
- These are **assumptions** regarding the missing data
- Not known causes of the missingness

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Missing Data Mechanisms

- Three Missing Data Mechanisms
 1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)

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Missing Data Mechanisms

- Three Missing Data Mechanisms
 1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)

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Missing Data Mechanisms

- A given analysis (e.g., *t*-test) ***inherently assumes*** a missing data mechanism
- If the assumption is incorrect, the parameter estimates may be biased

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Missing Data Mechanisms: MCAR

- Missingness on a variable Y_i is MCAR if the *probability* of missingness is *unrelated* to
 1. The values Y_i (including the missing values!)
 2. Or to any other variable in the analysis*

* You can have variables in your data set that are not in the analysis

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Missing Data Mechanisms: MCAR

- Missingness on a variable Y_i is MCAR if the *probability* of missingness is *unrelated* to
 1. The values Y_i (including the missing values!)
 2. Or to any other variable in the analysis*
- **The observed are a random sub-sample of the complete sample**

* You can have variables in your data set that are not in the analysis

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Complete Data

i	JS^{com}	IQ^{com}
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
19	16	118
20	12	134

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Complete Data			Observed Data		
i	JS^{com}	IQ^{com}	i	JS^{obs}	IQ^{obs}
1	9	78	1	--	78
2	13	84	2	13	84
3	10	84	3	--	84
4	8	85	4	8	85
5	7	87	5	7	87
6	7	91	6	7	91
7	9	92	7	9	92
8	9	94	8	9	94
9	11	94	9	11	94
10	7	96	10	--	96
11	7	99	11	7	99
⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118
20	12	134	20	--	134

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Complete Data			Observed Data			
i	JS^{com}	IQ^{com}	i	JS^{obs}	IQ^{obs}	JS^{ind}
1	9	78	1	--	78	1
2	13	84	2	13	84	0
3	10	84	3	--	84	1
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	7	91	0
7	9	92	7	9	92	0
8	9	94	8	9	94	0
9	11	94	9	11	94	0
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	--	134	1

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	13	84	0
3	10	84	3	--	84	1
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	7	91	0
7	9	92	7	9	92	0
8	9	94	8	9	94	0
9	11	94	9	11	94	0
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	--	134	1

MCAR:
Y^{com} is not related to Y^{ind}
or any other variable in the analysis

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	13	84	0
3	10	84	3	--	84	1
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	7	91	0
7	9	92	7	9	92	0
8	9	94	8	9	94	0
9	11	94	9	11	94	0
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	--	134	1

MCAR:
Y^{com} is not related to Y^{ind}

t-test:
Mean JS^{com} for JS^{ind} = 0
10.6

Mean JS^{com} for JS^{ind} = 1
9.6

p-value for difference
.3857

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	13	84	0
3	10	84	3	--	84	1
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	7	91	0
7	9	92	7	9	92	0
8	9	94	8	9	94	0
9	11	94	9	11	94	0
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	--	134	1

MCAR:
Y^{com} is not related to Y^{ind}
Or any other variable

t-test:
Mean IQ^{com} for JS^{ind} = 0
99.73

Mean IQ^{com} for JS^{ind} = 1
100.8

p-value for difference
.9235

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Missing Data Mechanisms: MCAR

- MCAR: missingness is not related to any variable in the data set
 - The observed are a random sample of your sample

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Missing Data Mechanisms: MCAR

- MCAR: missingness is not related to any variable in the data set
 - The observed are a random sample of your sample
- Can we ever know that data are MCAR in practice?

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Missing Data Mechanisms: MCAR

- MCAR: missingness is not related to any variable in the data set
 - The observed are a random sample of your sample
- Can we ever know that data are MCAR in practice?
 - *No, we would need the complete data*

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Missing Data Mechanisms

- Three Missing Data Mechanisms
 1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)

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Missing Data Mechanisms: MAR

- Missingness on a variable Y_i is **Missing at Random** if the probability of missingness is unrelated to Y_i **after controlling for other variables** in the analysis

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Missing Data Mechanisms: MAR

- Missingness on a variable Y_i is **Missing at Random** if the probability of missingness is unrelated to Y_i **after controlling for other variables** in the analysis
- Missingness on Y_i is related to another variable in the analysis
- You have other measures of the other variable

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Complete Data

i	JS ^{com}	IQ ^{com}
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
19	16	118
20	12	134

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Complete Data			Observed Data		
i	JS ^{com}	IQ ^{com}	i	JS ^{obs}	IQ ^{obs}
1	9	78	1	--	78
2	13	84	2	--	84
3	10	84	3	--	84
4	8	85	4	--	85
5	7	87	5	--	87
6	7	91	6	--	91
7	9	92	7	--	92
8	9	94	8	--	94
9	11	94	9	--	94
10	7	96	10	--	96
11	7	99	11	7	99
⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118
20	12	134	20	12	134

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Complete Data			Observed Data			
i	JS ^{com}	IQ ^{com}	i	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	--	84	1
3	10	84	3	--	84	1
4	8	85	4	--	85	1
5	7	87	5	--	87	1
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	--	94	1
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	--	84	1
3	10	84	3	--	84	1
4	8	85	4	--	85	1
5	7	87	5	--	87	1
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	--	94	1
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

MAR:
 Y^{com} is not related to Y^{ind}
 after controlling for other variables in the analysis

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	--	84	1
3	10	84	3	--	84	1
4	8	85	4	--	85	1
5	7	87	5	--	87	1
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	--	94	1
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

MAR:
 Y^{com} is not related to Y^{ind}
 after controlling for other variables in the analysis

$Y^{com} = b_0 + b_1 Y^{ind}$

	Est.	s.e.	p
b_0	11.7	.75	<.01
b_1	-2.7	1.05	.02

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	--	84	1
3	10	84	3	--	84	1
4	8	85	4	--	85	1
5	7	87	5	--	87	1
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	--	94	1
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

MAR:
 Y^{com} is not related to Y^{ind}
 after controlling for other variables in the analysis

$Y^{com} = b_0 + b_1 IQ^{obs}$

	Est.	s.e.	p
b_0	0.07	3.79	.98
b_1	.10	.04	.01

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	--	78	1
2	13	84	2	--	84	1
3	10	84	3	--	84	1
4	8	85	4	--	85	1
5	7	87	5	--	87	1
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	--	94	1
10	7	96	10	--	96	1
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

MAR:
 Y^{com} is not related to Y^{ind}
 after controlling for other variables in the analysis

$Y^{com} = b_0 + b_1 IQ^{obs} + b_2 Y^{ind}$

	Est.	s.e.	p
b_0	3.97	7.80	.62
b_1	.07	.07	.33
b_2	-1.11	1.92	.57

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Missing Data Mechanisms: MAR

- Missingness on random indicates that there is some other variable in the analyses that accounting for the missingness

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Missing Data Mechanisms: MAR

- Missingness on random indicates that there is some other variable in the analyses that accounting for the missingness
- *i.e., that variable can be a proxy for the cause of the missingness*
- *Once you account for that variable, you have a random sample again*

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Missing Data Mechanisms: MAR

- Can we ever know for certain that data are MAR?
- *No, we would need the complete data to be certain*
- *Even then, it would still be an assumption*

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Missing Data Mechanisms

- Three Missing Data Mechanisms
1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)

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Missing Data Mechanisms: MNAR

- Missingness on a variable Y_i is **Missing Not at Random** if the probability of missingness is **still related** to Y_i **after controlling for other variables** in the analysis

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Missing Data Mechanisms: MAR

- Missingness on a variable Y_i is **Missing Not at Random** if the probability of missingness is **still related** to Y_i **after controlling for other variables** in the analysis
- Missingness on Y_i is still related to Y_i after controlling for other variables

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Complete Data

i	JS^{com}	IQ^{com}
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
19	16	118
20	12	134

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Complete Data

i	JS^{com}	IQ^{com}
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
19	16	118
20	12	134

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Observed Data

i	JS^{obs}	IQ^{obs}
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	--	91
7	--	92
8	--	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
19	16	118
20	12	134

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Complete Data			Observed Data			
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}
1	9	78	1	9	78	0
2	13	84	2	13	84	0
3	10	84	3	10	84	0
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	11	94	0
10	7	96	10	7	96	0
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

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Complete Data			Observed Data				MNAR: Y^{com} is still related to Y^{ind} after controlling for other variables in the analysis
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}	
1	9	78	1	9	78	0	
2	13	84	2	13	84	0	
3	10	84	3	10	84	0	
4	8	85	4	8	85	0	
5	7	87	5	7	87	0	
6	7	91	6	--	91	1	
7	9	92	7	--	92	1	
8	9	94	8	--	94	1	
9	11	94	9	11	94	0	
10	7	96	10	7	96	0	
11	7	99	11	7	99	0	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
19	16	118	19	16	118	0	
20	12	134	20	12	134	0	

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Complete Data			Observed Data				MNAR: Y^{com} is still related to Y^{ind} after controlling for other variables in the analysis $Y^{com} = b_0 + b_1 Y^{ind}$
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}	
1	9	78	1	9	78	0	
2	13	84	2	13	84	0	
3	10	84	3	10	84	0	
4	8	85	4	8	85	0	
5	7	87	5	7	87	0	
6	7	91	6	--	91	1	
7	9	92	7	--	92	1	
8	9	94	8	--	94	1	
9	11	94	9	11	94	0	
10	7	96	10	7	96	0	
11	7	99	11	7	99	0	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
19	16	118	19	16	118	0	
20	12	134	20	12	134	0	

	Est.	s.e.	<i>p</i>
b_0	11.4	.51	<.01
b_1	-4.2	1.02	<.01

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Complete Data			Observed Data				MNAR: Y^{com} is still related to Y^{ind} after controlling for other variables in the analysis $Y^{com} = b_0 + b_1 IQ^{obs}$
<i>i</i>	JS ^{com}	IQ ^{com}	<i>i</i>	JS ^{obs}	IQ ^{obs}	JS ^{ind}	
1	9	78	1	9	78	0	
2	13	84	2	13	84	0	
3	10	84	3	10	84	0	
4	8	85	4	8	85	0	
5	7	87	5	7	87	0	
6	7	91	6	--	91	1	
7	9	92	7	--	92	1	
8	9	94	8	--	94	1	
9	11	94	9	11	94	0	
10	7	96	10	7	96	0	
11	7	99	11	7	99	0	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
19	16	118	19	16	118	0	
20	12	134	20	12	134	0	

	Est.	s.e.	<i>p</i>
b_0	0.07	3.79	.98
b_1	.10	.04	.01

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Complete Data			Observed Data			
i	JS^{com}	IQ^{com}	i	JS^{obs}	IQ^{obs}	JS^{ind}
1	9	78	1	9	78	0
2	13	84	2	13	84	0
3	10	84	3	10	84	0
4	8	85	4	8	85	0
5	7	87	5	7	87	0
6	7	91	6	--	91	1
7	9	92	7	--	92	1
8	9	94	8	--	94	1
9	11	94	9	11	94	0
10	7	96	10	7	96	0
11	7	99	11	7	99	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
19	16	118	19	16	118	0
20	12	134	20	12	134	0

MNAR:
 Y^{com} is still related to Y^{ind}
after controlling for other
variables in the analysis

$$Y^{com} = b_0 + b_1 IQ^{obs} + b_2 Y^{ind}$$

	Est.	s.e.	p
b_0	4.88	3.30	.16
b_1	.06	.03	.06
b_2	-3.48	1.01	<.01

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Missing Data Mechanisms: MNAR

- Data are missing not at random when the missingness on Y_i is related to the values of Y_i , even after controlling for other variables in the analysis

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Missing Data Mechanisms: MAR

- Missingness not at random occurs when the missingness on Y_i is related to the values of Y_i , even after controlling for other variables in the analysis
- i.e., the sample is still not a random sample from the population, even after accounting for other variables in the analysis*

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Missing Data Mechanisms: MAR

- Can we ever know for certain that data are MNAR?

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Missing Data Mechanisms: MAR

- Can we ever know for certain that data are MNAR?
- *No, we would need the complete data to be certain*
- *Even then, it would still be an assumption*

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Missing Data Mechanisms

- Three Missing Data Mechanisms
1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)

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Missing Data Mechanisms

1. Missing Completely at Random (MCAR)
 2. Missing at Random (MAR)
 3. Missing not at Random (MNAR)
- These are ***assumptions*** regarding missingness
 - Different statistical analysis will be valid under different assumptions

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Grand Overview

- Introduction to missing data
- Review of sampling
- Patterns, causes, and mechanisms of missing data
- The problem with missing data

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Missing Data Workshop
 Joint Doctoral Program in Clinical Psyc



The Problem with Missing Data

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Problems with Missing Data

- Most analytic techniques require complete data
 - Descriptive statistics (e.g., means, SDs, correlations)
 - *t*-tests
 - Significance testing of correlation
 - ANOVA
 - Regression

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Problems with Missing Data

- If our data contain missingness, then we typically perform listwise deletion

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Problems with Missing Data

- If our data contain missingness, then we typically perform listwise deletion
- If data are missing completely at random, then we should obtain unbiased estimates

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

- Missingness is MCAR
- Sub-sample is a random sample
- Parameter estimates are unbiased ☺
- Standard errors are still larger ☹

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample Remaining after Listwise Deletion

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	80
50	14	73

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Problems with Missing Data

- If our data contain missingness, then we typically perform listwise deletion
- If data are missing completely at random, then we should obtain unbiased estimated
- If data are missing at random or missing not at random then we will obtain biased estimates

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Population Data

<i>i</i>	JS	IQ
1	9	78
2	13	84
3	10	84
4	8	85
5	7	87
6	7	91
7	9	92
8	9	94
9	11	94
10	7	96
11	7	99
⋮	⋮	⋮
<i>N</i> -1	16	118
<i>N</i>	12	134

- Missingness is MAR or MNAR
- Sub-sample is not random a sample
- Parameter estimates can be biased ☹
- Standard errors are larger ☹

Random Sample

<i>i</i>	JS	IQ
1	10	72
2	12	74
3	7	90
⋮	⋮	⋮
99	9	118
100	14	134

Sample Remaining after Listwise Deletion

<i>i</i>	JS	IQ
1	10	72
⋮	⋮	⋮
49	9	80
50	14	73

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Problems with Missing Data

- Therefore, many analytic techniques assume data are missing completely at random
 - *And they didn't even tell you!*

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Problems with Missing Data

- So the major question is, is there anything we can do to at least assume MAR instead of the more restrictive MCAR?
 - *Multiple Imputation*

Grand Overview

- Introduction to missing data
- Review of sampling
- Patterns, causes, and mechanisms of missing data
- The problem with missing data