

Modern Strategies to Handle Missing Data: A Showcase of Research on Foster Children

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מכון חרוב (נ"ר)
The Haruv Institute (R.A.)

Modern Strategies to Handle Missing Data: A Showcase of Research on Foster Children

Issue:

Analysis of Data

How are you going to deal with missing data?

- A. I will only have a small number of missing data, so I will not deal with this missing data
- B. Pairwise deletion, listwise deletion or mean imputation
- C. Multiple imputation or FIML estimation
- D. I don't know yet
- E. Not applicable. I don't have / will not have missing data at all

www.menti.com; Code: 94 74 33

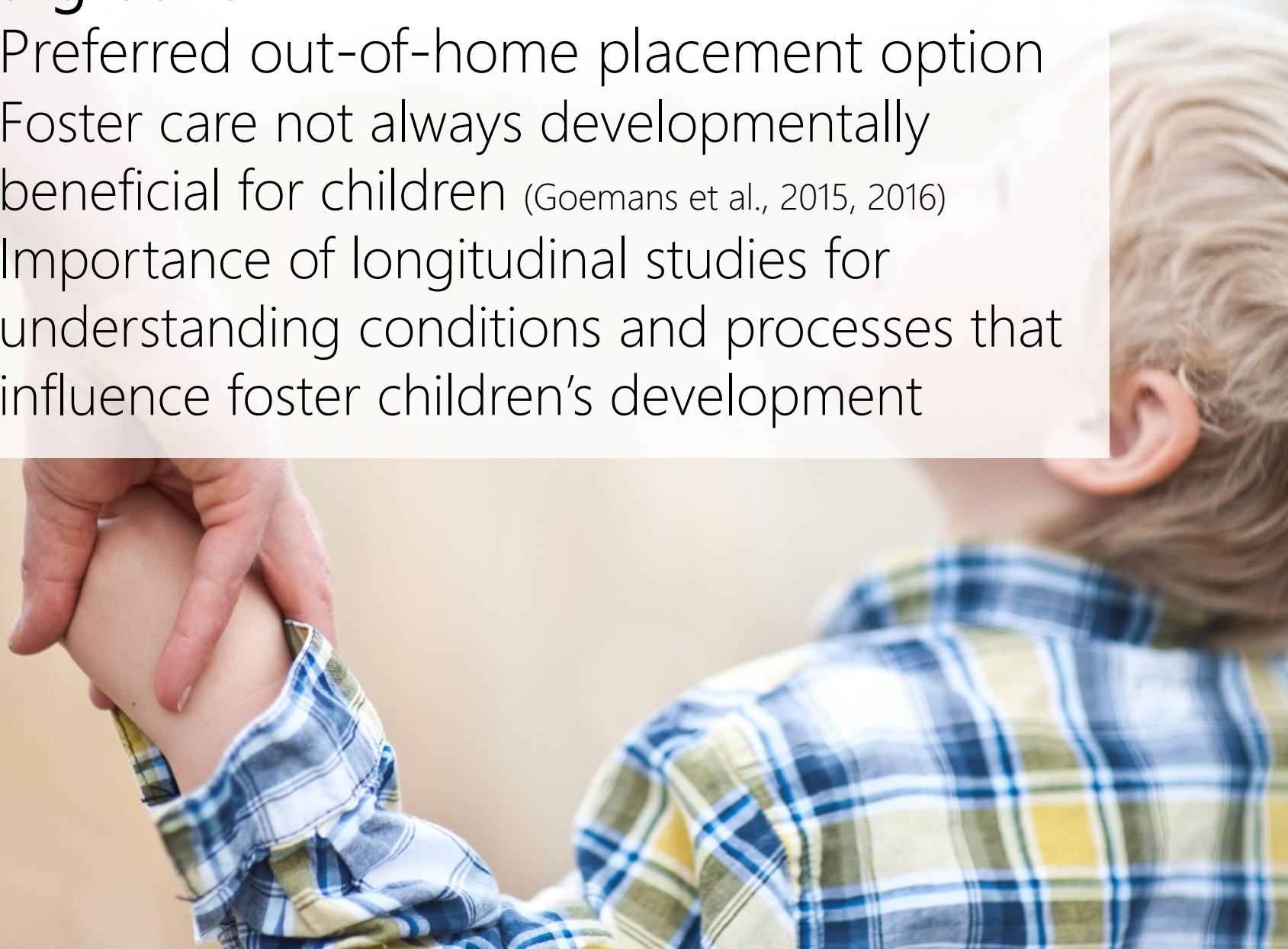
Today's Outline:

1. My PhD study
2. Missing data: an introduction
3. Two examples
4. Practical guidelines
5. Summary & Discussion



Background

- Preferred out-of-home placement option
- Foster care not always developmentally beneficial for children (Goemans et al., 2015, 2016)
- Importance of longitudinal studies for understanding conditions and processes that influence foster children's development



Method:
online
questionnaires

Design:
3-wave
longitudinal
study

Goal PhD study:
Examine which
factors are related
to foster children's
development





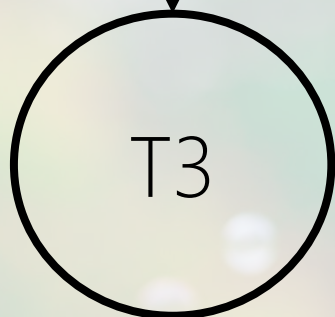
T1

- T1: October 2014 ($N = 446$)
Complete cases: $342/446 = 76.7\%$



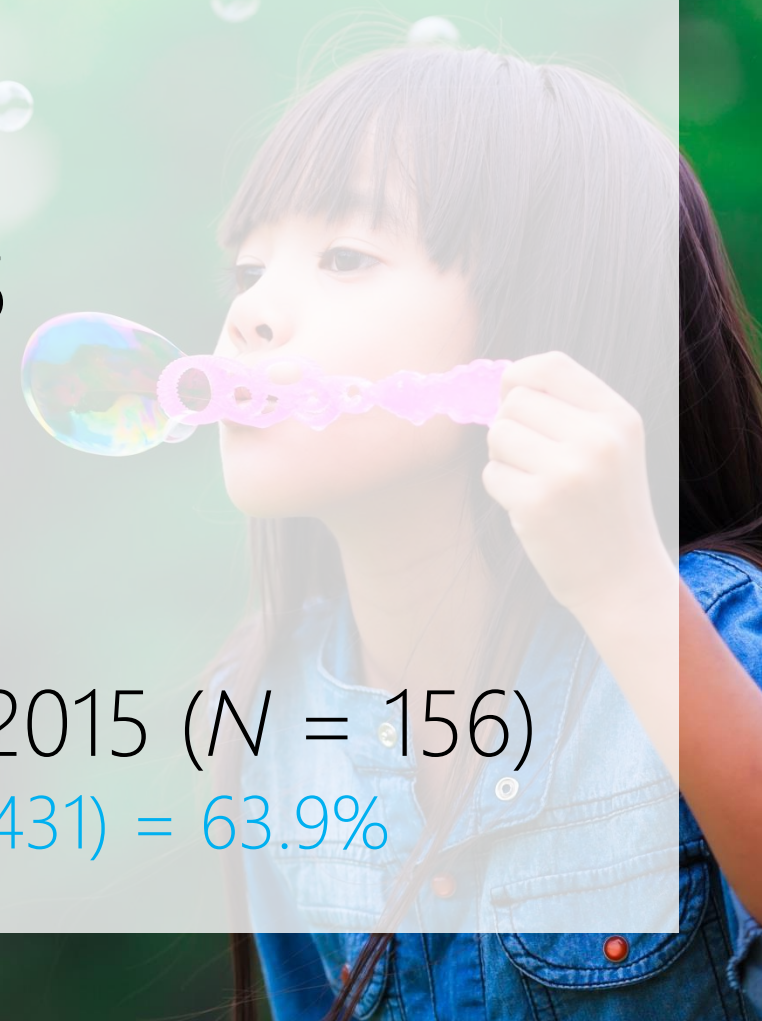
T2

- T2: April 2015



T3

- T3: October 2015 ($N = 156$)
Attrition: $100 - (156/431) = 63.9\%$



Example 2:
FIML
estimation

Example 1:
Multiple
imputation

Today:

Two examples of
modern strategies
to handle missing
data



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Missing data: an introduction

- Causes
- Consequences of missing data
- Missing data mechanisms:
 - MCAR
 - MAR
 - MNAR

Check this with Little's MCAR test: SPSS > Analyze > MVA / and other methods

- Ways to handle missing data
 - Traditional/simple methods – assumption: MCAR
 - Modern strategies – assumption: MCAR/MAR

Traditional/Simple methods

1. Listwise deletion – complete case analysis
2. Pairwise deletion – available case analysis
3. Mean substitution

Conclusions:

- All simple methods make strong and often unrealistic assumptions
- Listwise deletion is the least flawed, but very wasteful.
- Avoid and use modern techniques!





Modern methods

1. Hot deck imputation
2. EM algorithm
3. Multiple imputation (MI)
4. FIML methods

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Example 1: Overview

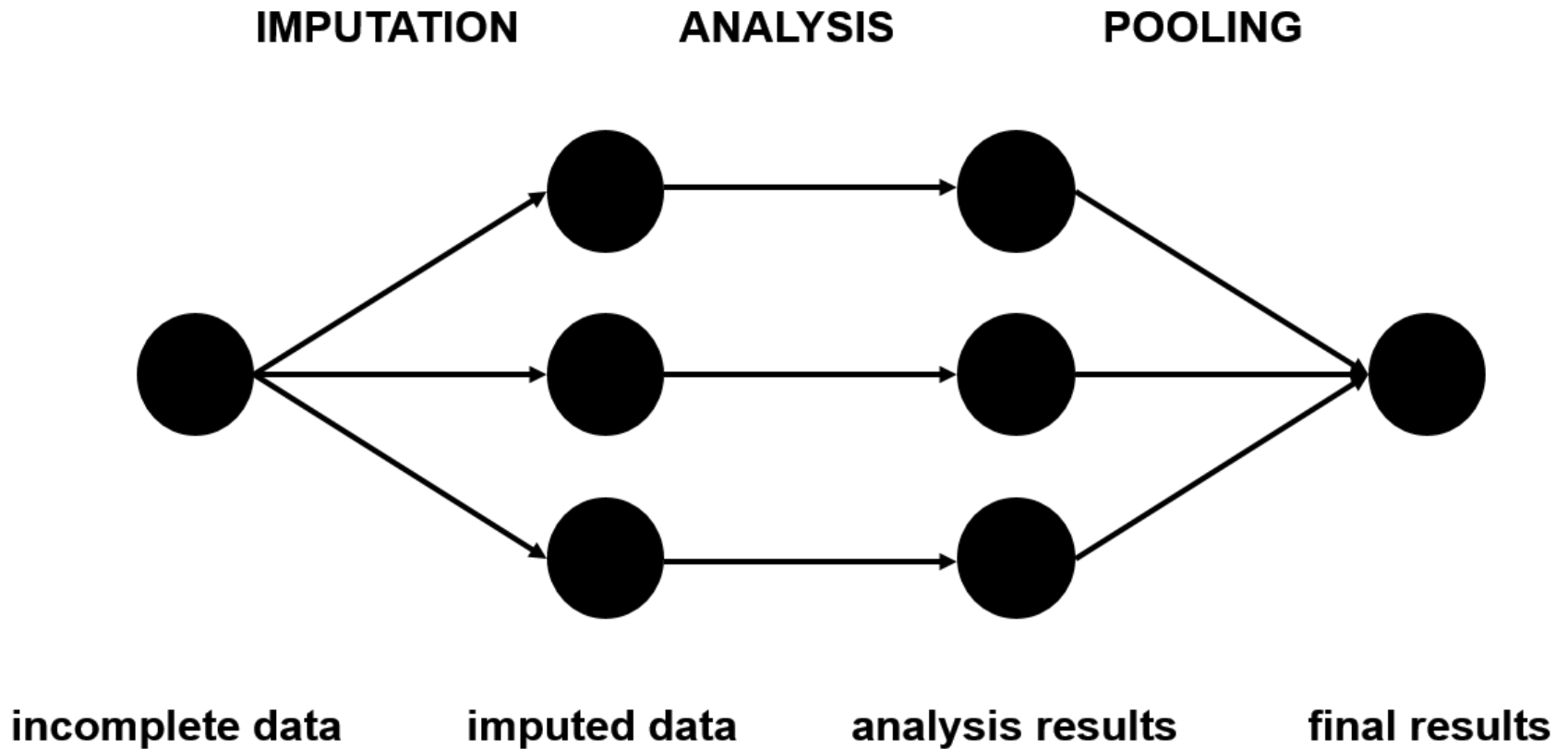
Research question	Which factors are related to foster children's psychosocial functioning? (Goemans et al., 2016)
Data	Wave I
Analysis	Hierarchical regression analysis
Software	SPSS
Type of missing data	Item nonresponse
Strategy	Multiple imputation

Example 1: Missing data

- Sample size: 446
- No more than 10% missing on each variable
- Range missing: 0-7.2%
- Mean missing: 2.0%
- Complete data for 342 (76.7%)



Multiple imputation










How to actually do it?

- Missing data mechanism? (MCAR or MAR?)
- SPSS: Analyze > Multiple imputation > Impute missing data values
 - Some suggestions:
 - Variables tab: use all variables, also DV (more reliable), 20 imputations (Graham et al., 2007)
 - Method tab: custom (MCMC), max iterations: 100, model type: dependent on multivariate normality

	SDQscale1	SDQ
189	3	
190	6	
191	.	
192	10	
193	3	
194	5	
195	.	
196	0	
197	2	
198	.	
199	4	
200	.	
201	6	
202	.	
203	8	
204	.	
205	9	
206	3	
207	1	
208	2	
209	2	

- Reports
- Descriptive Statistics
- Tables
- Compare Means
- General Linear Model
- Generalized Linear Models
- Mixed Models
- Correlate
- Regression
- Loglinear
- Neural Networks
- Classify
- Dimension Reduction
- Scale
- Nonparametric Tests
- Forecasting
- Survival
- Multiple Response
-  Missing Value Analysis...
- Multiple Imputation**
- Complex Samples
-  Simulation...
- Quality Control
-  ROC Curve...

Qscale4	SDQscale5	SDQext
4	5	6
6	3	9
.	.	.
2	9	14
1	7	7
7	7	12
.	.	.
2	8	2
0	7	1
.	.	.
1	9	0
.	.	.
.	.	.
8	6	9
.	.	.
6	6	3
.	.	.
.	.	9
.	.	1
2	5	5
2	5	13
4	7	15

-  Analyze Patterns...
-  Impute Missing Data Values...**

	Imputation_	UniekeCode	PZinstelling	Q6GeboortedatumPK	DatumEersteM eetmoment	Startdatum
1	0	1 3		05.11.2009	01.10.2014	1-Oct-2014 17:19:17
2	0	2 7		06.08.1999	01.10.2014	1-Oct-2014 17:10:42
3	0	3 3		03.06.2004	01.10.2014	1-Oct-2014 17:18:43
4	0	4 7		27.09.2002	01.10.2014	1-Oct-2014 17:16:04
5	0	5 6		25.08.2002	01.10.2014	1-Oct-2014 17:10:25
6	0	6 6		23.09.2009	01.10.2014	1-Oct-2014 17:15:40
7	0	7 6		08.10.2008	01.10.2014	1-Oct-2014 17:17:00
8	0	9 6		29.07.2004	01.10.2014	1-Oct-2014 17:31:06
9	0	10 2		29.09.2014	01.10.2014	1-Oct-2014 17:11:59
10	0	11 6		18.08.2004	01.10.2014	1-Oct-2014 17:25:51
11	0	13 3		11.02.2000	01.10.2014	1-Oct-2014 17:29:29
12	0	14 2		10.08.2009	01.10.2014	1-Oct-2014 17:07:35
13	0	15 7		10.07.2000	01.10.2014	1-Oct-2014 17:45:58
14	0	17 3		27.03.2000	01.10.2014	1-Oct-2014 18:21:38
15	0	18 7		30.06.1997	01.10.2014	1-Oct-2014 18:02:31
16	0	19 3		15.10.2005	01.10.2014	1-Oct-2014 18:06:43
17	0	20 7		05.05.1998	01.10.2014	1-Oct-2014 17:52:31
18	0	21 2		02.12.2002	01.10.2014	1-Oct-2014 18:09:24
19	0	22 7		01.05.1999	01.10.2014	1-Oct-2014 18:24:11

1

...

Data View

Variable View

Reports
Descriptive Statistics
Tables
Compare Means
General Linear Model
Generalized Linear Models
Mixed Models
Correlate

Regression

Loglinear

Neural Networks

Classify

Dimension Reduction

Scale

Nonparametric Tests

Forecasting

Survival

Multiple Response

Missing Value Analysis...

Multiple Imputation

Complex Samples

Simulation...

Quality Control

ROC Curve...

DatumEersteM eetmoment	Startdatum
01.10.2014	3-Oct-2014 14:08:53
01.10.2014	3-Oct-2014 14:54:30
01.10.2014	3-Oct-2014 16:25:38

Automatic Linear Modeling...
Linear...
Curve Estimation...
Partial Least Squares...
Binary Logistic...
Multinomial Logistic...
Ordinal...
Probit...
Nonlinear...
Weight Estimation...
2-Stage Least Squares...
Optimal Scaling (CATREG)...

01.10.2014	4-Oct-2014 23:51:34
01.10.2014	6-Oct-2014 09:56:55

Linear Regression

Gender
Q9Geboorteland...
Q9Geboorteland...
Q10Geboortelan...
Q10Geboortelan...
Q11Geboortelan...
Q11Geboortelan...
AutochtoonPK
Q12BioBrusjesPK
Q13GeloofPK
Q13GeloofPKAnd...
Q15Samenstellin...
Q15Samenstellin...
Samenstelling1of2
FamilyCompositi...
Q16Geboortedat...
Q17Geboortedat...
Q18Geboortelan...

Dependent:

SDQtotal

Block 1 of 1

Previous

Independent(s):

Age

Method:

Selection Variable:

Case Labels:

WLS Weight:

OK

Paste

Reset

Cancel

5-Oct-2014 20:30:12

1

1

5-Oct-2014 21:49:00

1

1

6-Oct-2014 08:56:04

1

2

6-Oct-2014 10:16:25

1

1

Coefficients^a

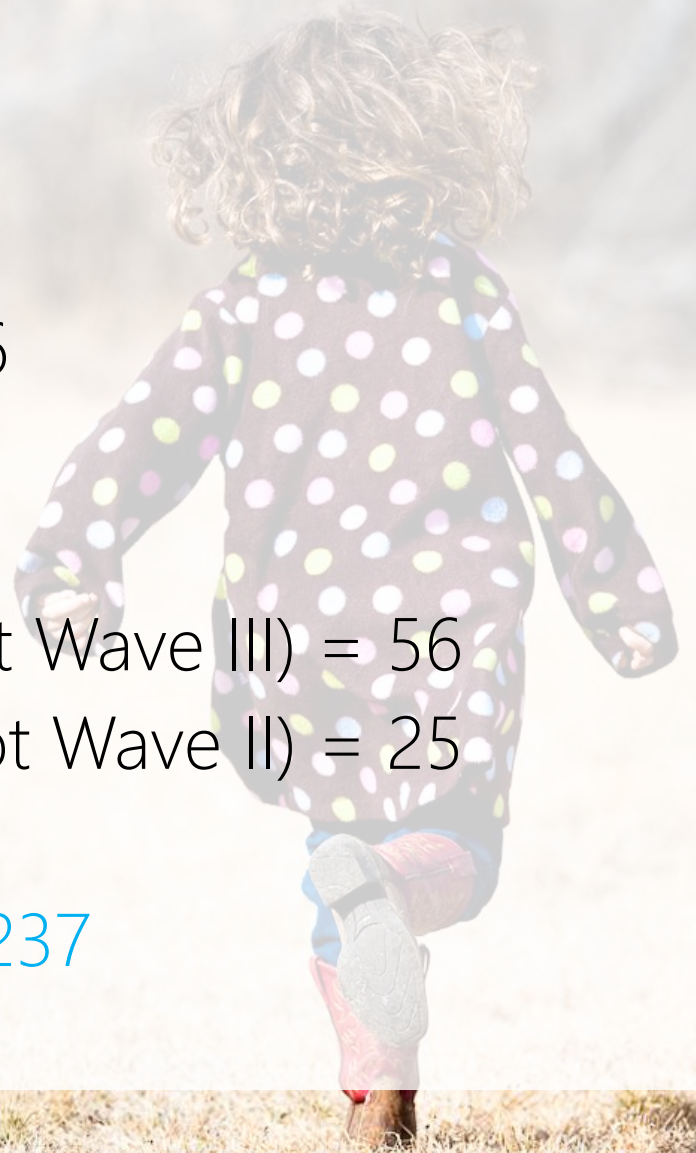
Imputation Number Model			Unstandardized Coefficients		Standardized Coefficients	t	Sig.	M
			B	Std. Error	Beta			
Original data	1	(Constant)	12,861	,862		14,912	,000	
		Leeftijd numeriek	-,046	,076	-,027	-,606	,545	
1	1	(Constant)	12,751	,859		14,849	,000	
		Leeftijd numeriek	-,038	,076	-,023	-,501	,617	
2	1	(Constant)	12,769	,859		14,863	,000	
		Leeftijd numeriek	-,040	,076	-,024	-,523	,601	
3	1	(Constant)	12,799	,860		14,888	,000	
		Leeftijd numeriek	-,042	,076	-,025	-,560	,576	
18	1	(Constant)	12,849	,862		14,902	,000	
		Leeftijd numeriek	-,047	,076	-,028	-,621	,535	
19	1	(Constant)	12,766	,859		14,856	,000	
		Leeftijd numeriek	-,039	,076	-,023	-,520	,604	
20	1	(Constant)	12,774	,858		14,881	,000	
		Leeftijd numeriek	-,040	,076	-,024	-,530	,596	
Pooled	1	(Constant)	12,806	,861		14,870	,000	
		Leeftijd numeriek	-,043	,076		-,568	,578	

Example 2: Overview

Research question	Are there transactional relations between foster children's internalizing and externalizing behaviors and foster parents' stress?
Data	Wave I, II, III
Analysis	Structural Equation Modeling (SEM)
Software	EQS
Type of missing data	Attrition (wave nonresponse)
Strategy	FIML estimation

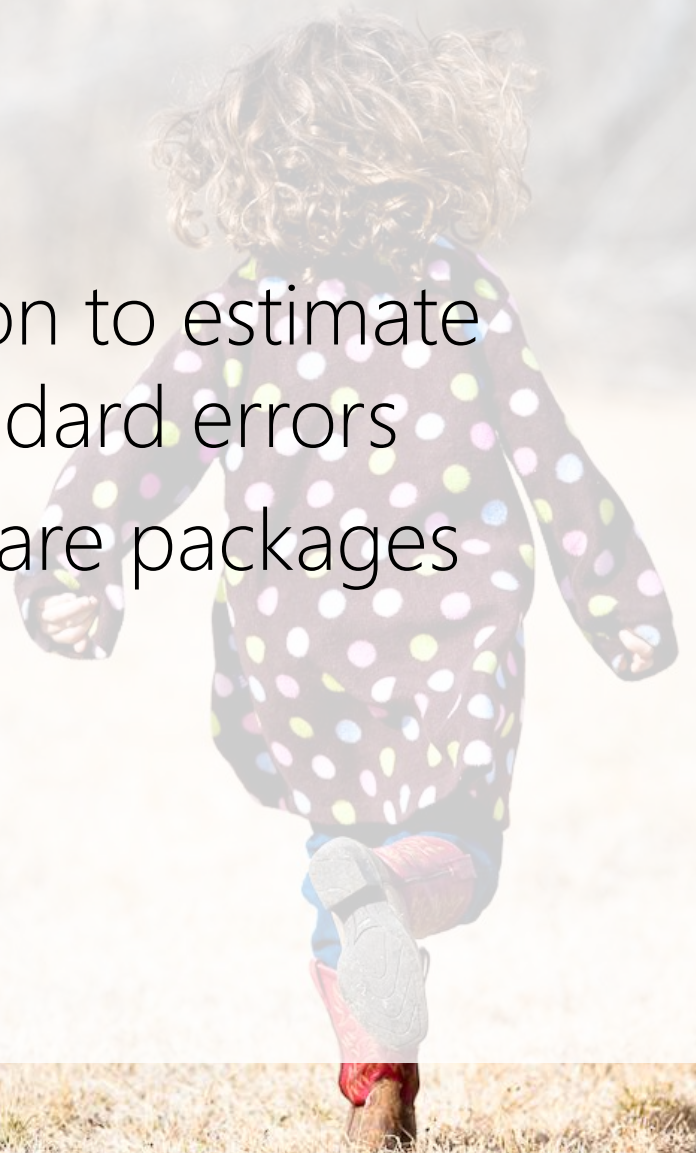
Example 2: Missing data

- Item nonresponse vs. attrition
- Original sample size: 431
- N present at Wave I, II, III = 156
- Attrition rate = 63.9%
- N present at Wave I and II (not Wave III) = 56
- N present at Wave I and III (not Wave II) = 25
- Final sample = $156 + 56 + 25 = 237$



FIML estimation:

- Does not impute data
- Use all available information to estimate parameter values and standard errors
- Available in the SEM software packages





How to actually do it?

- Missing data mechanism? (MCAR or MAR?)
- EQS
- Specifications:
 - MISSING=ML, SE=FISHER;
ANALYSIS=MOMENT
 - In case of non-multivariate normality:
METHODS=ML, ROBUST

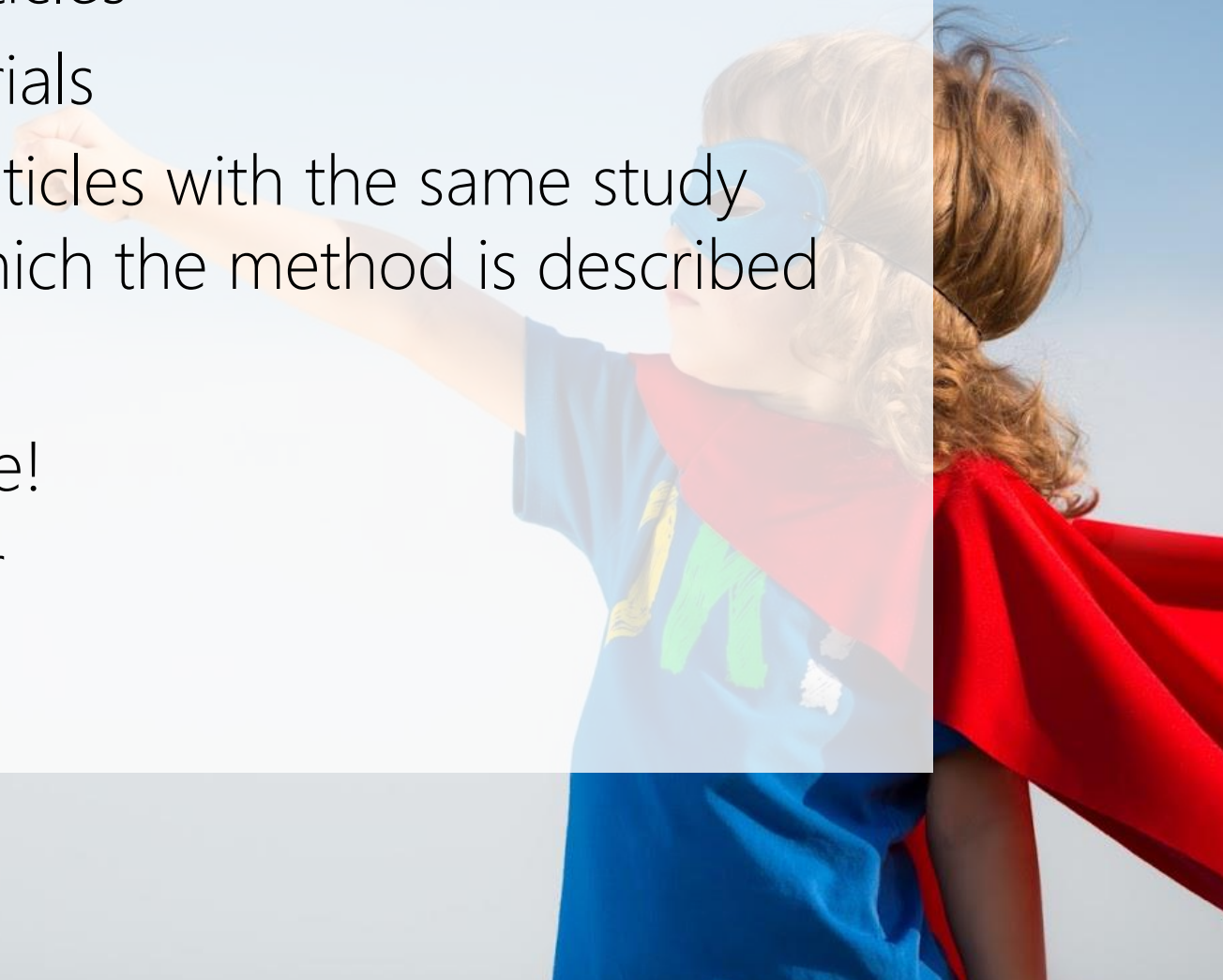
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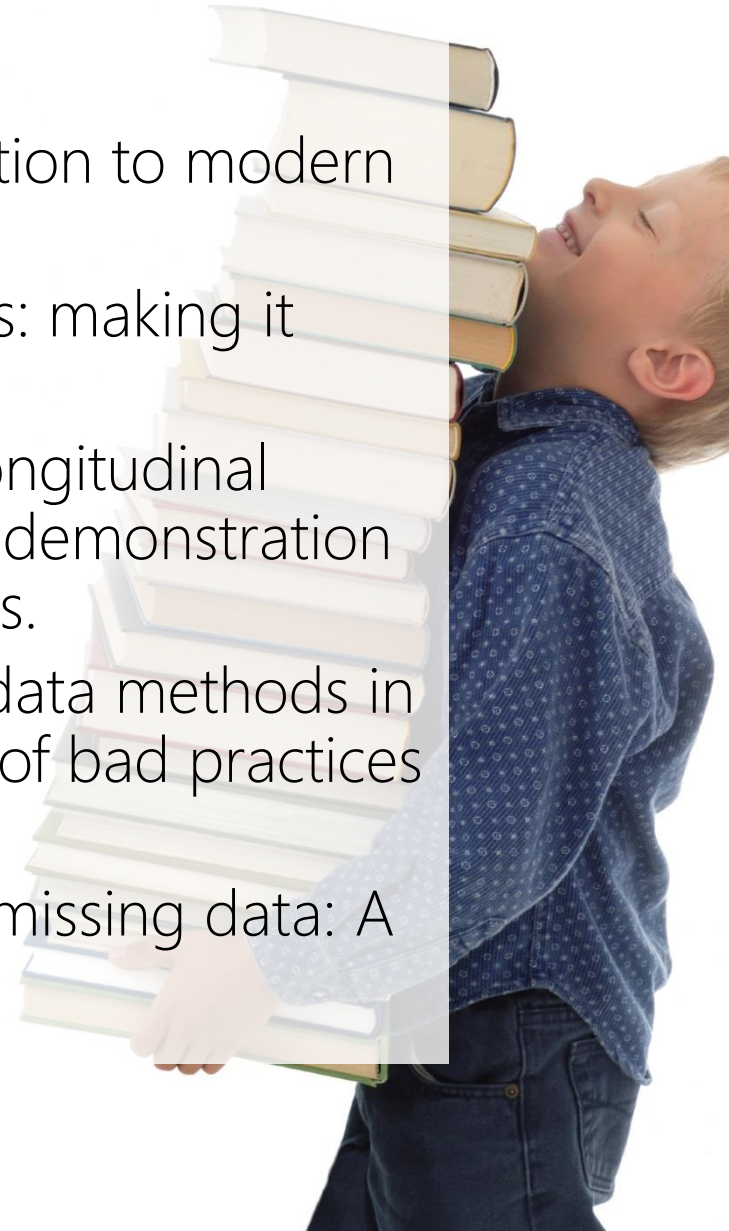
Suggestions for making it work:

- Books and articles
- YouTube tutorials
- Read other articles with the same study design / in which the method is described
- Take your time!
- Trial and error
- Ask for help



Further reading:

- Baraldi & Enders (2010). An introduction to modern missing data analyses.
- Graham (2009). Missing data analysis: making it work in the real world.
- Jackson et al. (2012). Strategies for longitudinal research with youth in foster care: A demonstration of methods, barriers, and innovations.
- Jellicic et al. (2009) – Use of missing data methods in longitudinal studies: the persistence of bad practices in developmental psychology.
- Peeters et al. (2015). How to handle missing data: A comparison of different approaches.



Guidelines for reporting:

- What did you do to prevent missing data?
- How much missing data do you have?
- What is the missing data mechanism?
- How did you handle the missing data?

Burton & Altman (2004); Jellicic et al. (2009); Peeters et al. (2014), Peugh & Enders (2004); Schlomer et al. (2010)

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PROS

CONS

- MI and FIML best methods currently available
- General methods

- More work
- More complex?

Use of Missing Data Methods in Longitudinal Studies: The Persistence of Bad Practices in Developmental Psychology

“Modern” Missing Data Analysis Methods

deletion “are or which is that 10 years applications.”
However, the ML and MI methods yield more valid results than listwise and pairwise deletion approaches and, therefore, should become part of the developmental scientist’s analytical tool kit.

Developmental Psychology
2009, Vol. 45, No. 4, 1195–1199

appearing with greater frequency in published research articles, a substantial gap still exists between the procedures that the methodological literature recommends and those that are actually used in the applied research studies

these method
data so that a

John W. Graham

J.W. Graham, *Missing Data*

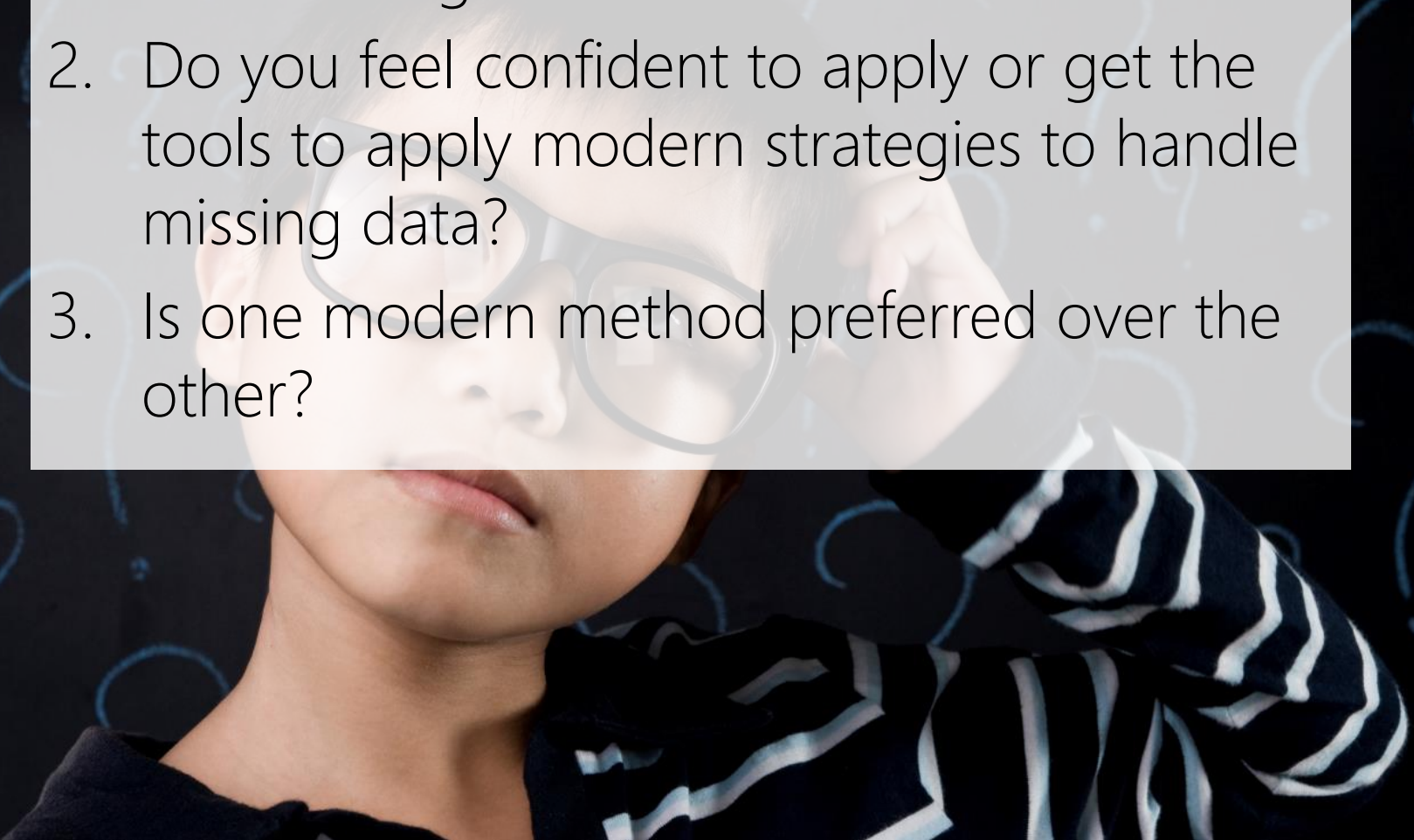
Vote again!

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- B. Pairwise deletion, listwise deletion or mean imputation
- C. Multiple imputation or FIML estimation
- D. I don't know yet
- E. Not applicable. I don't have / will not have missing data at all

www.menti.com; Code: 94 74 33

Discussion:

1. What did you already know about dealing with missing data?
2. Do you feel confident to apply or get the tools to apply modern strategies to handle missing data?
3. Is one modern method preferred over the other?



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Thank you for your attention!

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