A structured framework for assessing sensitivity to missing data assumptions in longitudinal clinical trials

C. H. Mallinckrodt, Q. Lin ,G. Molenberghs Pharmaceut. Statist. 2013, 12 1–6

Outline

- Background
- Analytic Road Map
- Example

History

- Lots of recent research
- Research fostered updated guidance
- Considerable agreement between NRC guidance PhRMA Expert group, CHMP Points to consider
- We largely agree on what to do in theory
- Now we need to bring the theory into practice

3 Pillars of Dealing with Missing Data

- Clear objectives and causal estimands
- Limit missing data
- Sensible primary analysis supported by sensitivity analyses
 - Methods driven by plausible scientific assumptions
 - Sensitivity analyses assess robustness to departures from assumptions

Acknowledgements

- DIA Scientific Working Group
- Programs freely available at missingdata.org.uk
- Specific thanks
 - Michael O'Kelly
 - Bohdana Ratitch
 - James Roger
 - Pierre Bunouf

Quintiles Dublin Ireland

Quintiles Saint-Laurent, Québec, Canada,

London School of Hygiene & Tropical Medicine

Laboratoires Pierre Fabre, Toulouse, France

Outline

- Background
- Analytic Road Map
- Example

Missing Data in Clinical Trials

- Efficacy outcomes are seldom MCAR because the observed outcomes typically influence dropout (DC for lack of efficacy)
- Trials are designed to observe all the relevant information, which minimizes MNAR data
- Hence in the highly controlled scenario of longitudinal confirmatory trials, missing data may be mostly MAR

Modeling Conundrum

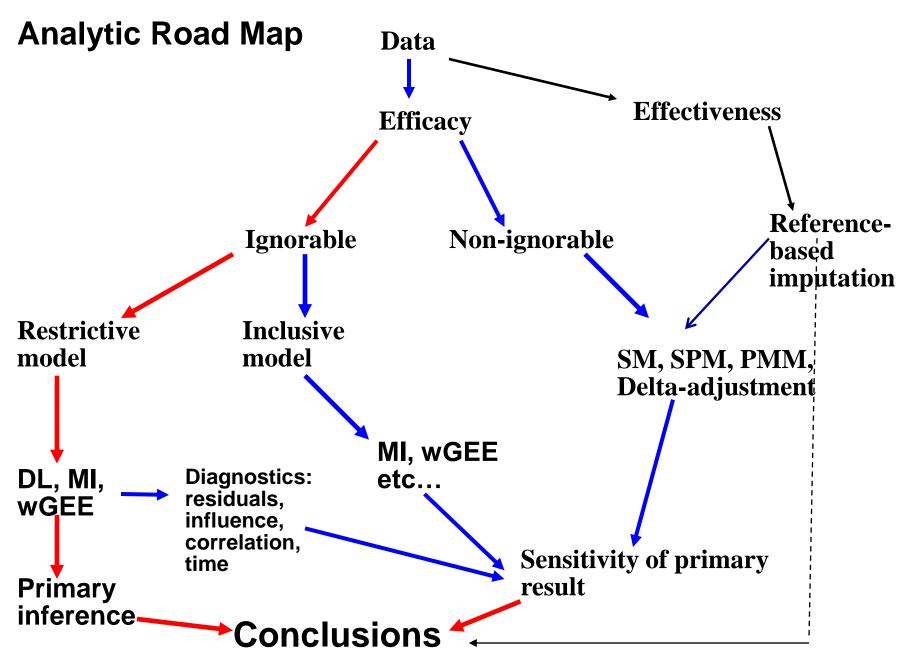
- Can't assume MCAR
- We don't have the missing data about which the assumptions are made, Therefore...
- Validity of MAR can't be verified; i.e., MNAR can not be ruled out
- Key assumptions in MNAR models can't be verified

Modeling Considerations

- Can do better than MAR only via assumptions
- Sensitivity to violations of assumptions and model misspecification more severe in MNAR
- No individual MNAR analysis is definitive

General Guidance

- Strive for validity of MAR primary analysis
- Implement MNAR model(s) under varying but plausible assumptions
- Compare results from assuming MAR vs. various MNAR implementations



Selection Models

- Joint model
 - Primary analysis (same or similar model)
 - logistic regression for probability of dropout
 - Dropout and measurement models linked as primary outcome is predictor of dropout

Pattern Mixture Models

- Assesses the outcome variable separately for different groups (patterns), often defined by time of drop-out, and then combines results across groups for final inference
- Assesses consequences when distribution of unobserved data ≠ what it would have been if observed

Controlled Imputations: New Methods in the PMM Framework

- Assumptions can be transparent and debated
- General idea is to create departures from MAR
 - Plausible worst case
 - Progressive stress test
- Based on standard MI
 - Reference-based
 - Delta adjustment

Controlled Imputations: Reference Based

- Jump to reference
 - The statistical behavior of drug treated patients after dropout <u>immediately becomes</u> that of reference patients" (e.g., placebo)
 - Use for drugs with short on target half-life
- Copy reference
 - ...gradually transitions to placebo
 - Use for drugs with long on target half-life
- Copy increment
 - After dropout, change for drug = change for placebo
 - Use for disease modifying drugs

Mechanics of Reference-based Imputations

- Similar to "Standard" MI, except
 - Parameters for imputation model obtained from only the reference (control/placebo) group
 - Missing data for both reference and drug group are imputed based on the imputation model derived from placebo data

Contexts for Reference-based Imputations

- Effectiveness context
 - Assumes benefit diminishes / disappears
 - Accounts for study effect & placebo effect
 - Valid if patients improve or worsen
 - Free of confounds in follow up data
- Efficacy context
 - Worst reasonable case MNAR
- Standard software, standard tests

Controlled Imputations: Delta Adjustment

- Visit-by-Visit
 - Subtract a constant (delta) from visit X imputed value that then further influences imputed values at visit > X
 - First missing visit only
 - All missing visits
 - Progressively increase delta until conclusion from primary analysis is overturned
- After completion of all imputations

Outline

- Background
- Analytic Road Map
- Example

Example Data from Major Depression

- Two real but contrived data sets (n=100/arm)
- Drug arm patients randomly selected from 3 active arms
- Placebo arms mostly as is (with minor replication)
- Nearly identical designs
 - 8-week, double blind, randomized 1:1:1:1
 - Assessments @ weeks 1,2,4,6,8
 - Similar inclusion / exclusion
 - Low dropout from EU study with ext and titration
 - High dropout from US fixed dose, no extension

Example Data

- High dropout
 - Completion rates: placebo 60%, drug 70%
 - 1000 planned observations, 850 available
- Low dropout
 - Completion rates: placebo 92%, drug 92%
 - 1000 planned observations, 961 available

Example From A Depression Trial

- Primary objective: test the difference between drug and placebo in mean change to planned endpoint
 - de-jure (efficacy) hypothesis
 - ... when taken as directed
- Secondary objective:
 - de-facto (effectiveness) hypothesis
 - ... as actually taken

Patient Retention

			Wee	k	
	1	2	4	6	8
High drop	<u>out</u>				
Placebo	8	7	12	13	60
Drug	9	6	10	5	70
Low Drope	<u>out</u>				
Placebo	2	0	3	3	92
Drug	2	1	2	3	92

Prior to week 8 these values are the number of dropouts. For week 8 the values are the number of completers because week 8 is the last scheduled assessment.

Primary Analysis: Direct Likelihood

Random effects modeled as part of within subject errors. Full multivariate model: unstructured modeling of time and correlation.

Primary Results: Endpoint Contrast

	LSME	AN Change			
Data	Drug	Placebo	Diff	SE	P value
<u>High</u>	8.24	5.94	<u>2.29</u>	1.00	0.024
Low	12.32	10.50	1.82	0.70	0.010

Correlation Sensitivity Results

CORR	AIC	Estimate	StdErr	P Value	
<u>High dropout</u>					
UN	4679.82	2.2928	1.0024	0.0240	
UN EMPIRICAL	4679.82	2.2928	0.9794	0.0202	
TOEPH	4684.44	2.1003	0.9148	0.0231	Range in
TOEPH EMPIRICAL	4684.44	2.1003	0.9278	0.0239	estimates nearly
TOEPH GROUP=TRT	4689.88	1.8207	0.9139	0.0482	7x greater from
UN GROUP=TRT	4692.05	1.9622	1.0059	0.0535	high dropout
CSH	4735.81	1.8689	0.9330	0.0471	
CSH EMPIRICAL	4735.81	1.8689	0.9169	0.0419	
CSH GROUP=TRT	4739.34	<u>1.6973</u>	0.9323	0.0708	
Low dropout					
UN GROUP=TRT	4861.70	<u>1.8535</u>	0.7034	0.0092	
UN	4867.68	1.8150	0.6995	0.0103	
UN EMPIRICAL	4867.68	1.8150	0.6669	0.0071	
_	•	•	•	•	
CSH	5030.40	<u>1.7653</u>	0.7054	0.0132	

Selection Model Results Summary

Range of outcomes from endpoint contrast in selection model results using "plausible MNAR" inputs

Endpoint Contrasts							
<u>Data</u>	Lowest plausible	Highest plausible					
High dropout	1.30	3.60					
Low dropout	1.71	2.01					

Range in estimates nearly 8x greater in high dropout

Selection Model Results – <u>high dropout</u>

0.2 0.2 0.0 0.2 -0.2 0.2	Week 8 LS Placebo 4.87 5.60 6.28 6.76	MEANS Drug 7.33 7.38 7.41 7.42	Endpoint Contrast 2.46 1.78 1.18 0.66	Standard Error 1.09 1.05 1.05 1.06	P value 0.023 0.091 0.282 0.527
0.2 0.0	4.94	7.97	3.03	1.07	0.005
0.00.0	5.63	8.00	2.37	1.04	0.022
- 0.2 0.0	6.29	8.04	1.75	1.02	0.087
-0.4 0.0	6.75	8.05	1.30	1.02	0.204
0.0 -0.2 · · · · · · · · · · · · · · · · · · ·	4.97 5.67 6.31 6.76	8.57 8.57 8.59 8.63	3.60 2.89 2.29 1.86	1.06 1.03 1.01 1.01	0.001 0.004 0.024 0.064
0.0 -0.4 :	4.97 5.68 6.33	8.97 8.96 8.98	4.01 3.28 2.64	1.07 1.03 1.01	<0.001 0.002 0.009
-0.4 -0.4	6.78	9.01	2.22	1.01	0.027

- 1. Ψ_5 and Ψ_6 are the regression coefficients (placebo and drug, respectively) for the association between the current, possibly missing efficacy scores and the logit for probability of dropout
- 2. This combination of values is not plausible based on previous experience but is included for completeness of illustration.

Selection Model Results - <u>high dropout</u>

Input Values $\Psi_5^1 \ \Psi_6^1$ 0.2 0.2 0.0	Week 8 Placebo 4.87 5.60	LSMEANS Drug 7.33 7.38	Endpoint Contrast 2.46 1.78	Standard Error 1.09 1.05	P value 0.023 0.091
-0.2 0.2	6.28	7.41	1.18	1.05	0.282
-0.42 0.22	6.76	7.42	0.66	1.06	0.527
0.2 0.0	4.94	7.97	3.03	1.07	0.005
0.0 0.0	5.63	8.00	2.37	1.04	0.022
- 0.2 0.0	6.29	8.04	1.75	1.02	0.087
-0.4 0.0	6.75	8.05	1.30	1.02	0.204
0.2 -0.2	4.97	8.57	3.60	1.06	0.001
0.0 -0.2	5.67	8.57	2.89	1.03	0.004
-0.2 -0.2	6.31	8.59	2.29	1.01	0.024
-0.4 -0.2	6.76	8.63	1.86	1.01	0.064
$0.2^2 0.4^2 \ 0.0 -0.4$	4.97 5.68	8.97 8.96	4.01 3.28	1.07 1.03	<0.001 0.002
-0.2 -0.4	6.33	8.98	2.64	1.01	0.002
-0.4 -0.4	6.78	9.01	2.22	1.01	0.027

- With equal negative (positive) values for Ψ_5 and Ψ_6 the within group mean changes were greater (less) than from MAR
- Little impact on endpoint contrasts with equal values for Ψ_5 and Ψ_6 . But with more dropout on placebo, slight decrease in endpoint contrast with equal negative values for Ψ_5 and Ψ_6

Selection Model Results - high dropout

Input Values $\Psi_5^1 \ \Psi_6^1$ 0.2 0.2 0.0 0.2 -0.2 0.2 -0.4 0.2	Week 8 Placebo 4.87 5.60 6.28 6.76	Drug 7.33 7.38 7.41 7.42	Endpoint Contrast 2.46 1.78 1.18 0.66	Standard Error 1.09 1.05 1.05 1.06	P value 0.023 0.091 0.282 0.527
0.2 0.0	4.94	7.97	3.03	1.07	0.005
0.0 0.0	5.63	8.00	2.37	1.04	0.022
-0.2 0.0	6.29	8.04	1.75	1.02	0.087
-0.4 0.0	6.75	8.05	1.30	1.02	0.204
0.2 -0.2	4.97	8.57	3.60	1.06	0.001
0.0 -0.2	5.67	8.57	2.89	1.03	0.004
-0.2 -0.2	6.31	8.59	2.29	1.01	0.024
-0.4 -0.2	6.76	8.63	1.86	1.01	0.064
0.2 ² -0.4 ²	4.97	8.97	4.01	1.07	<0.001
0.0 -0.4	5.68	8.96	3.28	1.03	0.002
-0.2 -0.4	6.33	8.98	2.64	1.01	0.009
-0.4 -0.4	6.78	9.01	2.22	1.01	0.027

- Negative Ψ means subjects with negative residuals more likely to withdraw, leading to decreased observed mean. The selection model compensates by increasing the LSMEAN.
- Corresponding change to endpoint contrast

Selection Model Results - high dropout

Input Values $\Psi_5^1 \ \Psi_6^1$ 0.2 0.2 0.00.2 -0.2 0.2 -0.42 0.22	S Week 8 Placebo 4.87 5.60 6.28 6.76	Drug 7.33 7.38 7.41 7.42	Endpoint Contrast 2.46 1.78 1.18 0.66	Standard Error 1.09 1.05 1.05 1.06	P value 0.023 0.091 0.282 0.527	• ne
0.2 0.0	4.94	7.97	3.03	1.07	0.005	w
0.0 0.0	5.63	8.00	2.37	1.04	0.022	ok
- 0.2 0.0	6.29	8.04	1.75	1.02	0.087	m
- 0.4 0.0	6.75	8.05	1.30	1.02	0.204	th
0.2 -0.2	4.97	8.57	3.60	1.06	0.001	• (
0.0 -0.2	5.67	8.57	2.89	1.03	0.004	
- 0.2 -0.2	6.31	8.59	2.29	1.01	0.024	
-0.4 -0.2	6.76	8.63	1.86	1.01	0.064	
0.2 ² -0.4 ² 0.0 -0.4 -0.2 -0.4 -0.4 -0.4	4.97 5.68 6.33 6.78	8.97 8.96 8.98 9.01	4.01 3.28 2.64 2.22	1.07 1.03 1.01 1.01	<0.001 0.002 0.009 0.027	

- Negative Ψ means subjects with negative residuals more likely to withdraw, leading to an decreased observed mean. The selection model compensates by increasing the LSMEAN.
- Corresponding change to endpoint contrast

Pattern Mixture Model Results

High dropout

Identifying	Endpoint	Standard	
Restriction ¹⁻³	Contrast	Error	P value
ACMV	2.67	1.17	0.0224
CCMV	2.51	1.05	0.0166
NCMV	2.87	1.69	0.0895

- 1. ACMV = available case missing values
- 2. CCMV = complete case missing values
- 3. NCMV = neighboring case missing values

Low Dropout

Number of patients in patterns insufficient to estimate parameters

Reference-Based Imputation Results

	LSMEANS		LSMEAN	Std		
	Placeb	o Drug	Difference ¹	Error	P value	
High dropout						
MAR	-5.95	-8.24	2.29	1.00	0.024	
J2R	-5.97	-7.57	1.60	0.99	0.110	
CR	-5.96	-7.71	1.75	0.98	0.075	
CIR	-5.95	-7.78	1.83	0.97	0.004	
Low dropout						
MAR	-10.56	-12.40	1.84	0.70	0.009	
J2R	-10.55	-12.26	1.71	0.70	0.016	
CR	-10.55	-12.27	1.72	0.70	0.015	
CIR	-10.55	-12.27	1.72	0.70	0.015	

Difference MAR vs. J2R over 6x greater in high dropout

Delta-adjustment Results

Low Dropout			High dropout			
Value of	Endpoint	Std		Endpoint	Std	
Delta	Contrast	Error	Pvalue	Contrast	Error	PValue
0	1.85	0.71	0.009	2.31	1.02	0.024
0.5	1.77	0.71	0.013	2.00	1.03	0.051
2.0	1.52	0.73	0.037			
2.5	1.44	0.74	0.051			

- Delta required to overturn significance of primary result
 5x larger for high dropout data set
- Change in endpoint contrast per 1 unit change in Delta
 - Low dropout = 0.16
 - High dropout = 0.62

Discussion

- Proper sensitivity analyses allow us to <u>assess</u> sensitivity
- Lower rates of dropout is the only way to <u>improve</u> sensitivity
- Controlled imputations are useful and intuitive