

# Evaluation of approaches for multiple imputation in three-level data structures

**Rushani Wijesuriya**

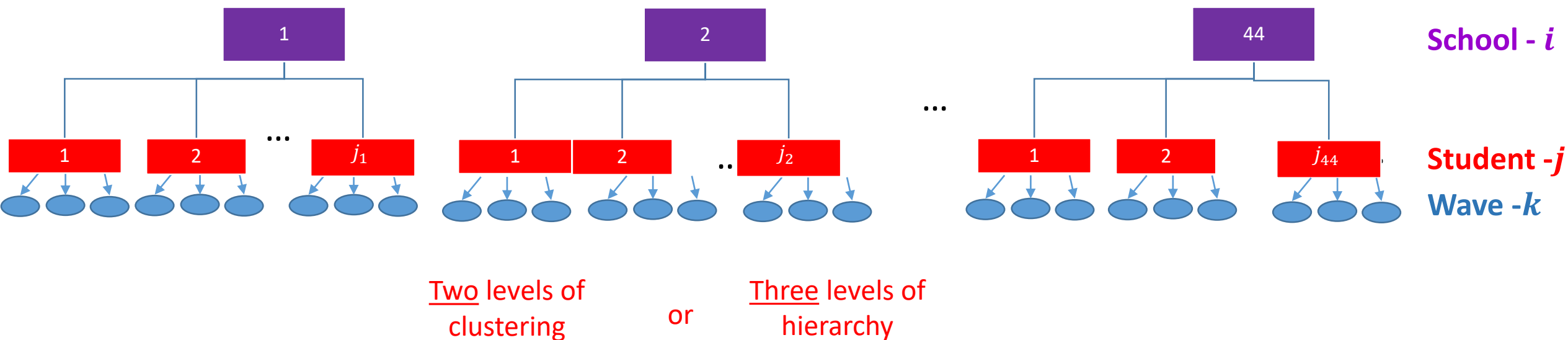
Supervisors :

A/Prof Katherine Lee, Dr. Margarita Moreno-Betancur, Prof John Carlin and  
Dr. Anurika De Silva

24<sup>th</sup> of September 2019

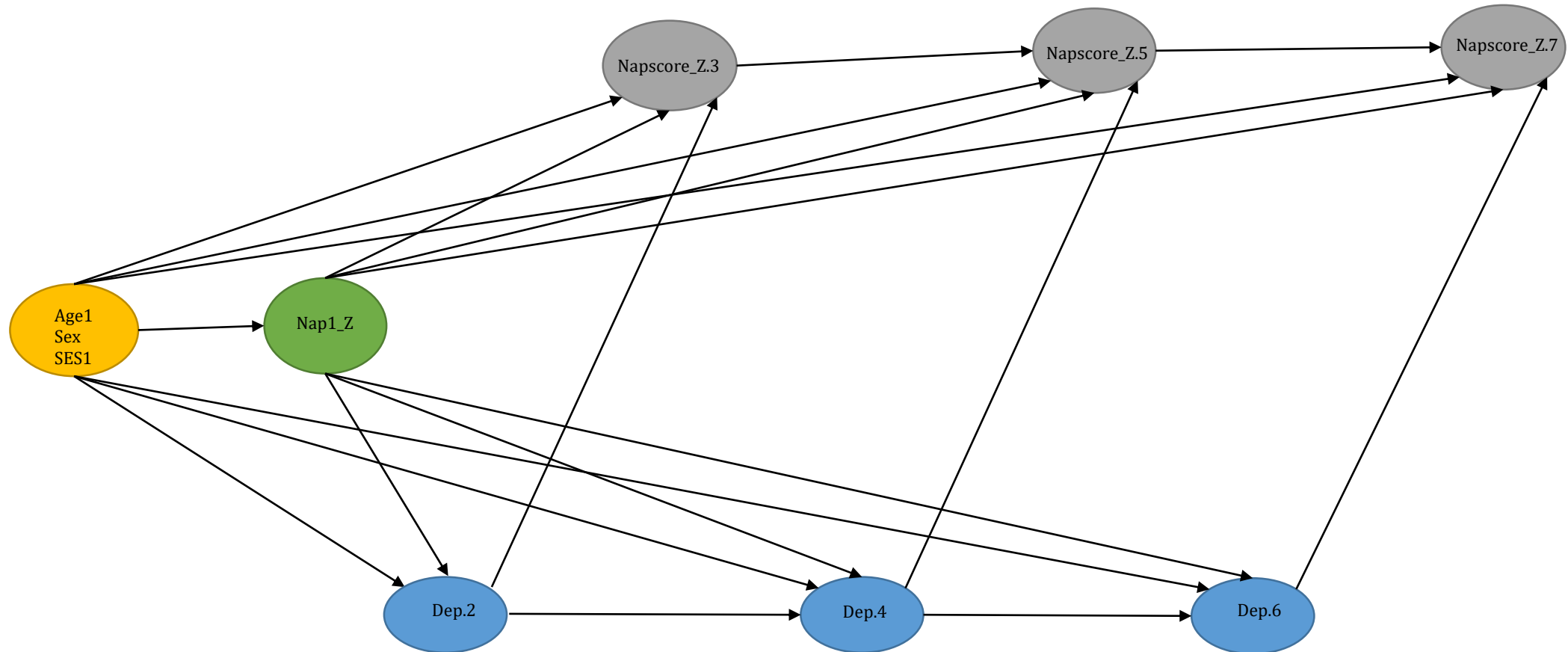


# Case Study: Childhood to Adolescence Transition Study (CATS)



- Repeated measures within an individual and also clustering by school

# Case Study : Target Analysis and Missing Data



# Multiple Imputation

---

- MI is a two stage approach with a separate imputation stage and an analysis stage
- A key consideration in MI : the imputation model needs to preserve all the features of the analysis
- Need to incorporate the clustered structure in the imputation model

# Multiple Imputation for multilevel data

How to incorporate the multilevel structure in the imputation model?

Manipulate the standard (single-level) MI approaches

- The Dummy Indicator (DI) approach
- Just Another Variable (JAV) approach (if repeated measures are at fixed intervals of time)

Wide format  
one row per individual

| ID | Age | Sex    | Dep_1 | Dep_2 | Dep_3 |
|----|-----|--------|-------|-------|-------|
| 1  | 8   | Male   | 0.4   | 1.9   | 0.2   |
| 2  | 7   | Female | 1.9   | -     | 2.9   |
| 3  | 9   | Male   | 1.0   | 3.1   | -     |
| 4  | 8   | Male   | -     | 2.6   | -     |
| 5  | 10  | Female | 1.5   | 0.5   | 1.5   |

MI approaches based on mixed effects /multilevel models

| ID | Age | Sex    | Wave | Dep |
|----|-----|--------|------|-----|
| 1  | 8   | Male   | 1    | 0.4 |
| 1  | 8   | Male   | 2    | 1.9 |
| 1  | 8   | Male   | 3    | 0.2 |
| 2  | 7   | Female | 1    | 1.9 |
| 2  | 7   | Female | 2    | -   |
| 2  | 7   | Female | 3    | 2.9 |

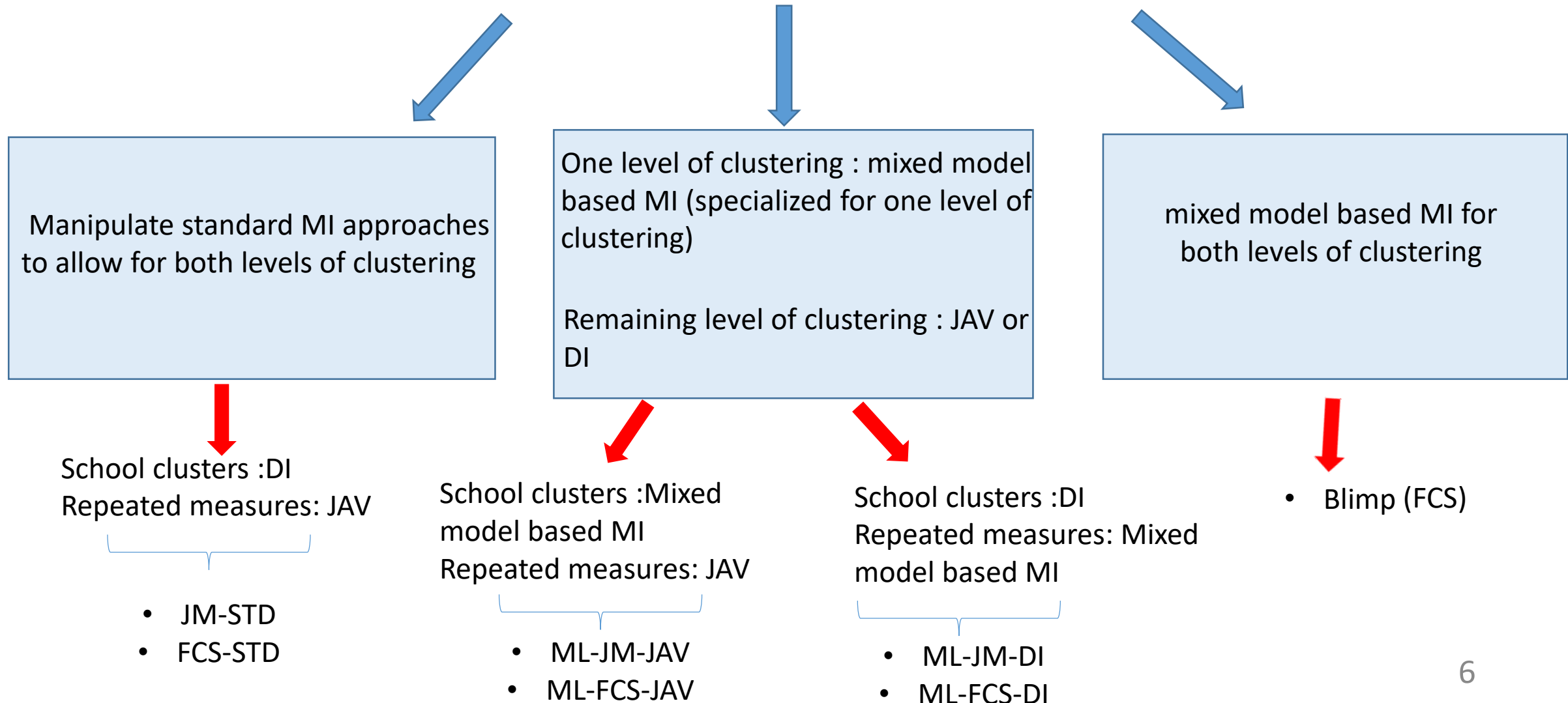
Long format

One row per wave per individual

Structure used in the analysis stage

# Multiple Imputation for three-level data

How to impute incomplete three-level data?



# Simulation of Complete Data

---

- 1000 datasets were simulated
- 40 school clusters ( $i = 1, \dots, 40$ ) were generated
- Each school cluster was populated in two ways: Fixed, Varying
- Four different strengths of level-2 and level-3 intra-cluster correlations

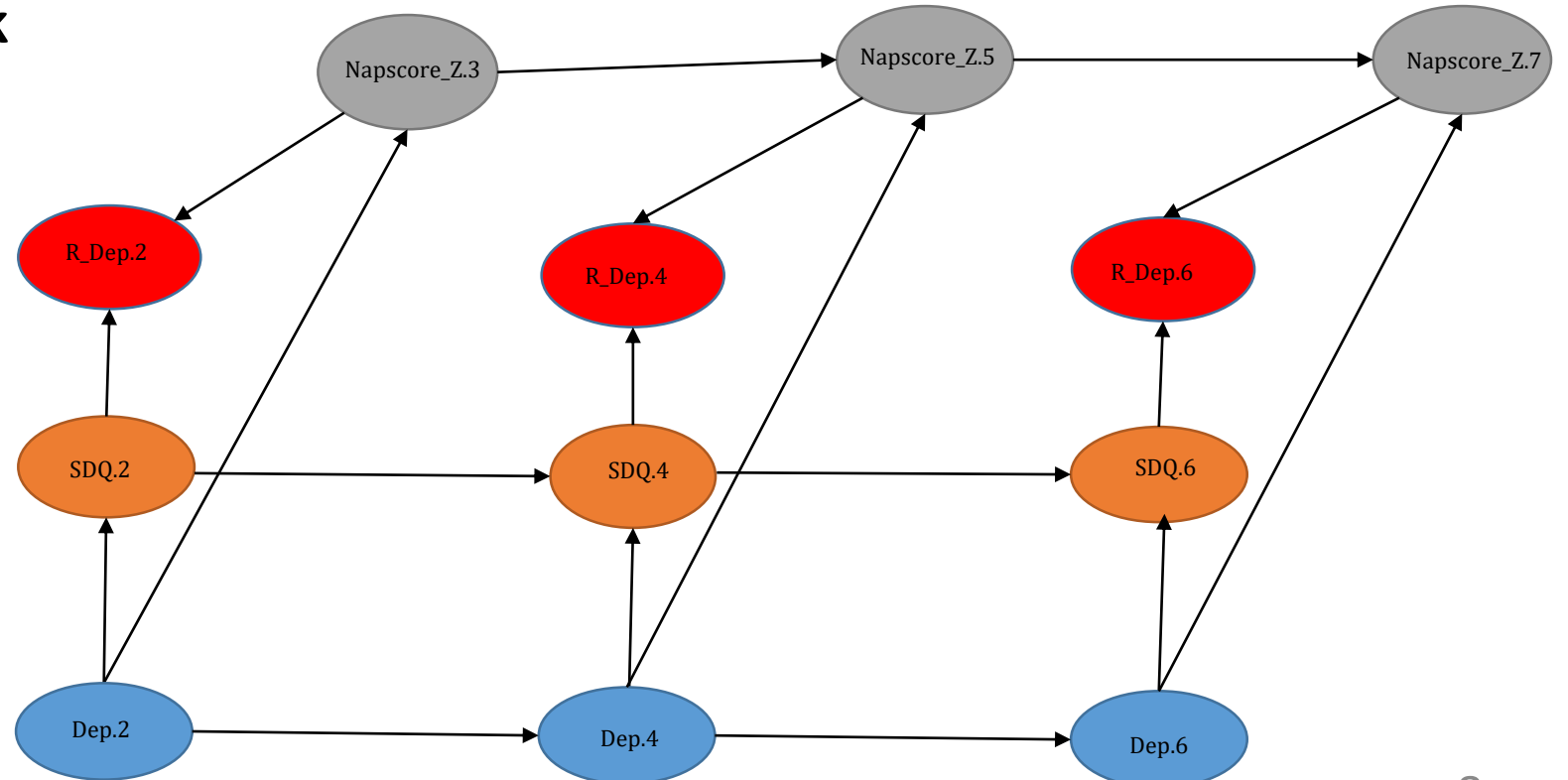
|           | ICC                     |                              |
|-----------|-------------------------|------------------------------|
|           | level 3 (within school) | level 2 (within individual ) |
| High-high | 0.15                    | 0.5                          |
| High-low  | 0.15                    | 0.2                          |
| Low-high  | 0.05                    | 0.5                          |
| Low-low   | 0.05                    | 0.2                          |

# Generation of Missing Data

**MCAR**  
Missing values assigned completely at random

10% ← Dep.2 → 20%  
15% ← Dep.4 → 30%  
20% ← Dep.6 → 40%

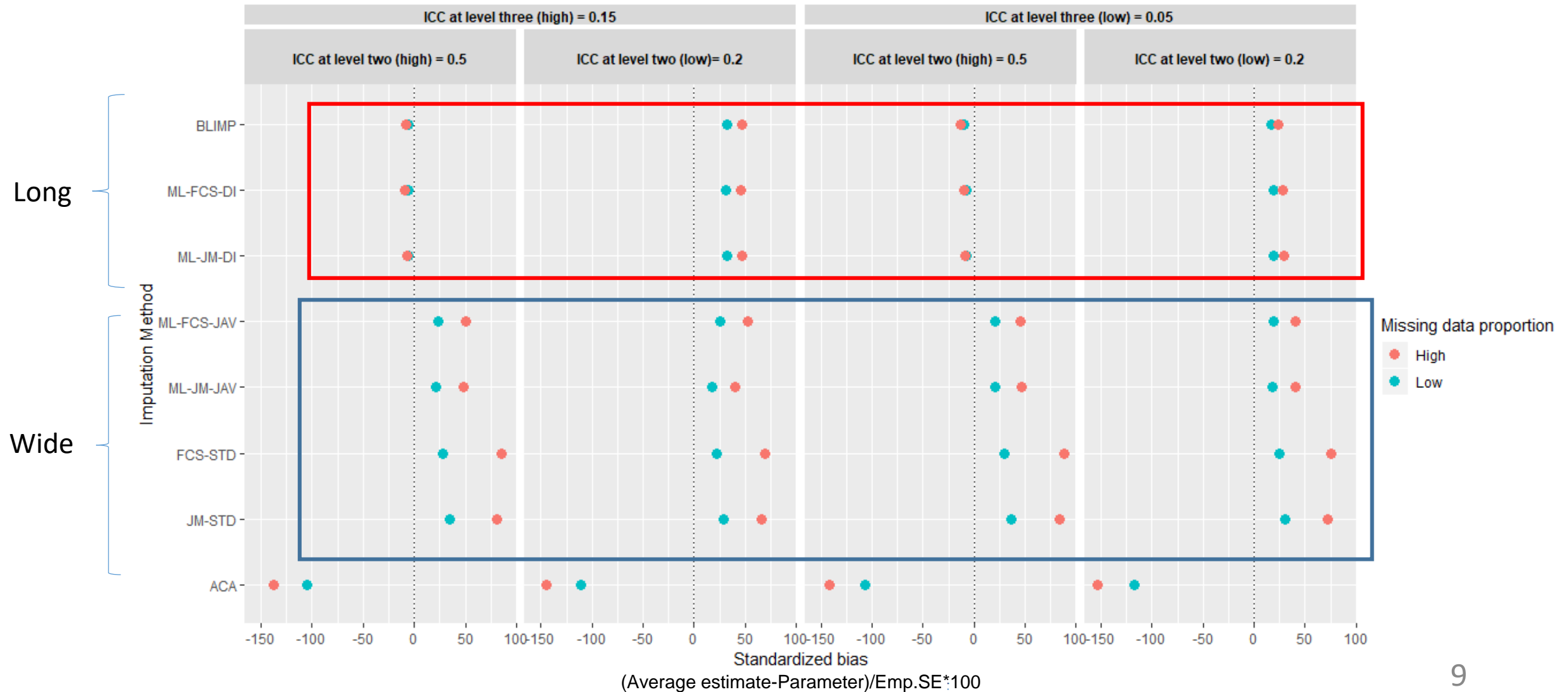
**MAR- Strong**  
**MAR- Weak**





# Simulation Study-Results

Standardized biases for the regression coefficient  $\beta = (-0.5)$  - MAR (strong)



# Key findings

---

- Approaches which imputes in long format (BLIMP, ML-JM-DI, ML-FCS-DI) were the best in estimating the effect estimate
- These approaches are also less sensitive to the missing data proportion
- However, ML-JM-DI and ML-FCS-DI can be problematic when the number of clusters is high

# Acknowledgements

---

- Statistical Society of Australia, Victorian Branch
- Supervisors
- VicBiostat



# Thank You

You can download the slides at :

<https://www.slideshare.net/secret/svP7lOllC00zzS>

You can contact me anytime at : [rushani.wijesuriya@mcri.edu.au](mailto:rushani.wijesuriya@mcri.edu.au)

