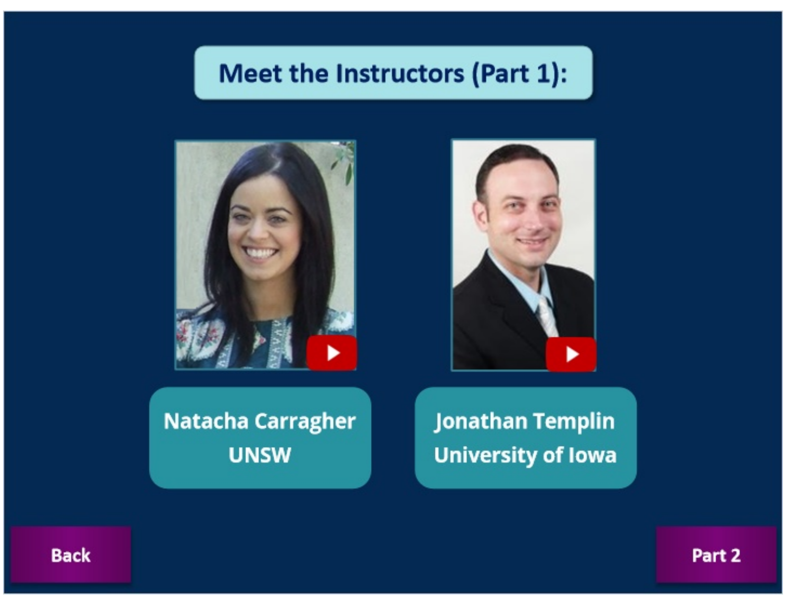
DM04 SLIDES (DCM Checklists, Version 1.4)

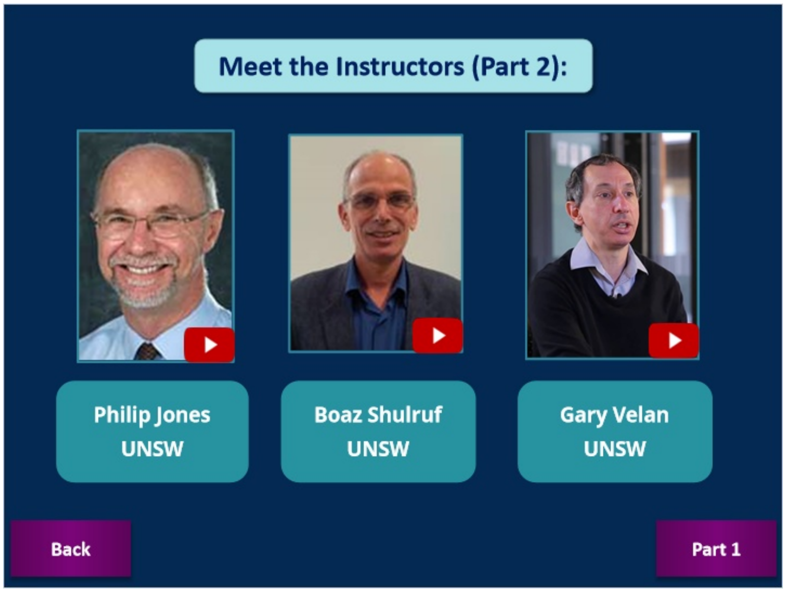
1. Module Overview

1.1 Module Cover (START)

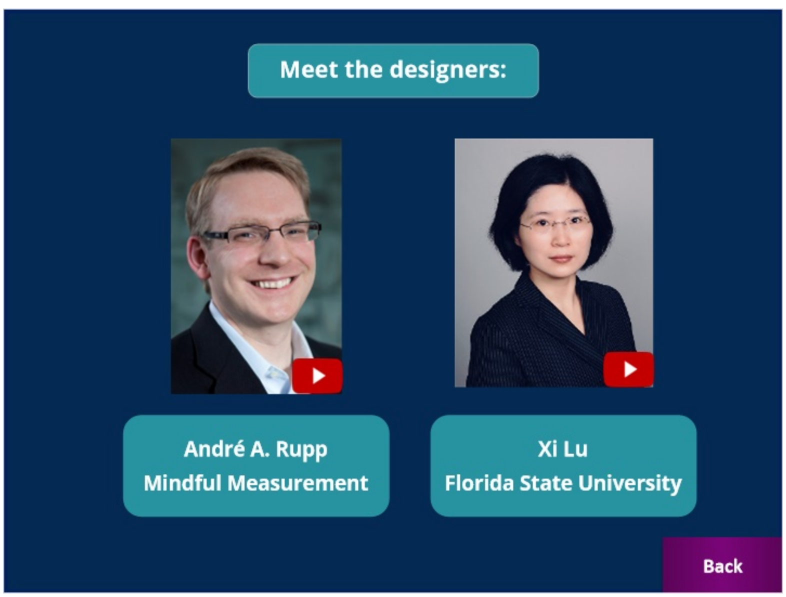
1.2 Instructors (I)



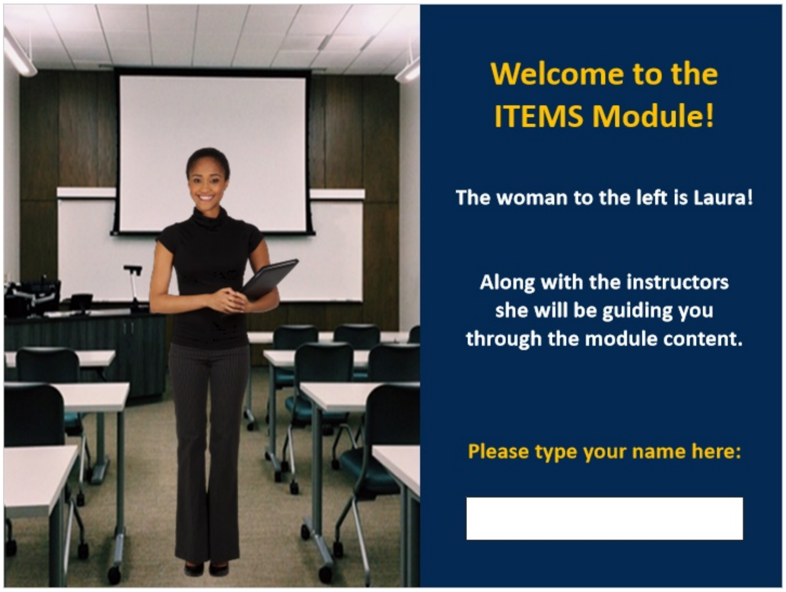
1.3 Instructors (II)



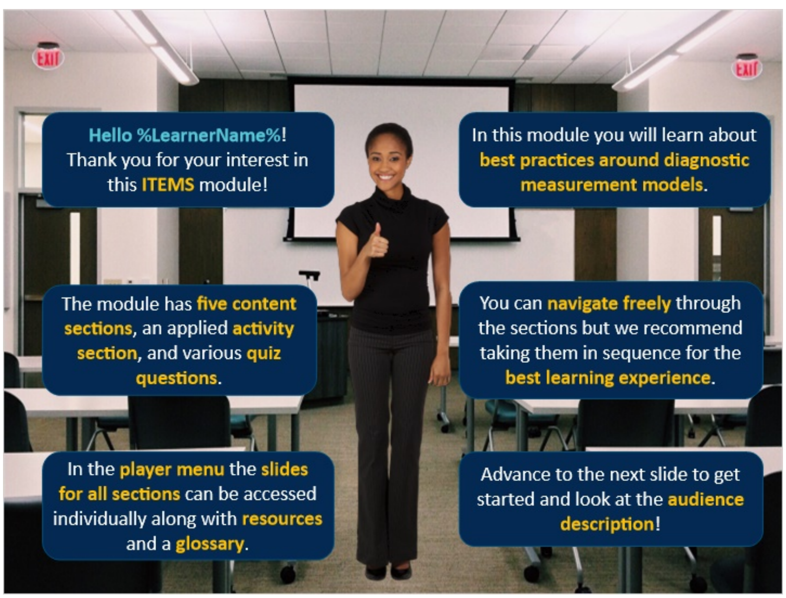
1.4 Designers



1.5 Welcome

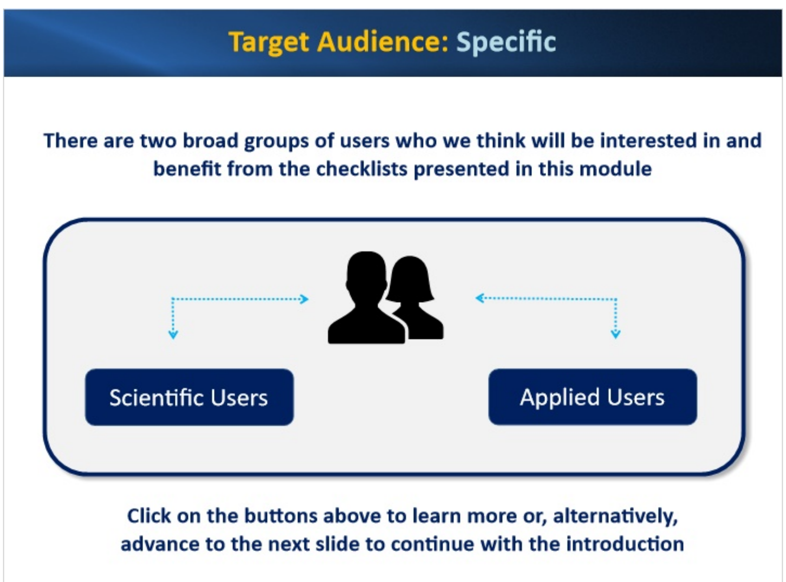


1.6 Overview



1.7 Target Audience: General

1.8 Target Audience: Specific



1.9 Target Audience: Scientific Users

Target Audience: Scientific Users

Estimating DCMs requires the use of **specialized software** (e.g., **Mplus, SAS, R**), **significant time investment**, as well as **psychometric expertise / experience**

Therefore, we envision that the '**Estimation**', '**Model Fit Evaluation**' and '**Interpretation**' checklists will mostly likely appeal to **scientific users**

These include:

- data analysts / scientists
- research assistants or research scientists
- psychometricians and other measurement professionals
- graduate students in Master's, Ph.D. or certificate programs

1.10 Target Audience: Applied Users

Target Audience: Applied Users

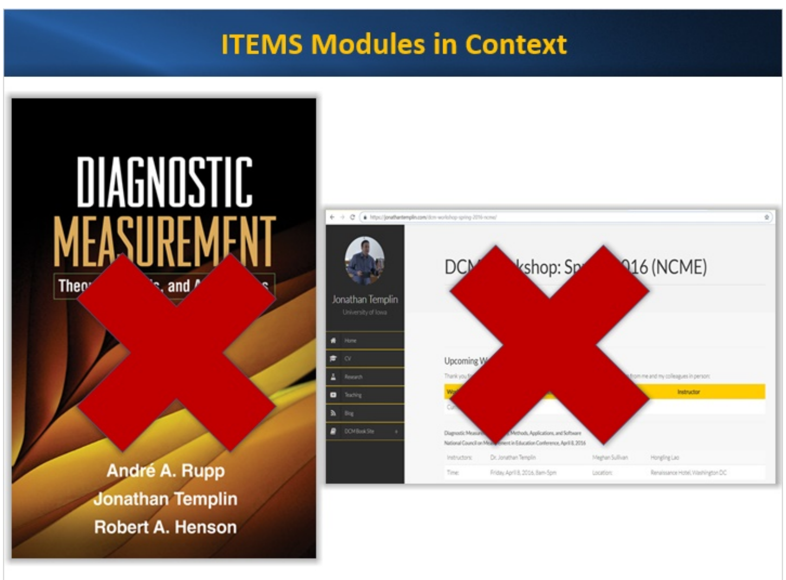
The '**Reporting**' checklist is general and provides a **template for reviewing the quality of the methodology and reporting** of DCM studies

Therefore we envisage that this checklist will likely appeal to **applied users**:

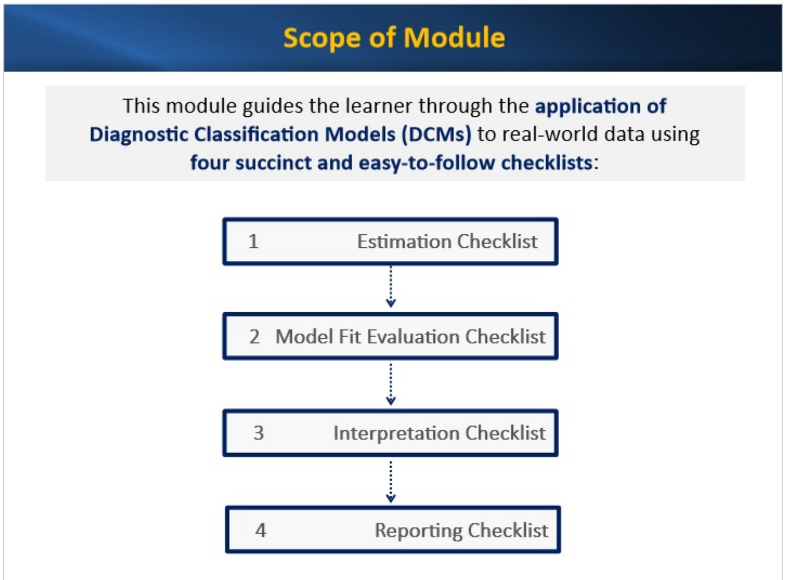
- journal editors
- peer reviewers
- funding agencies
- readers

1.11 Scope (I)

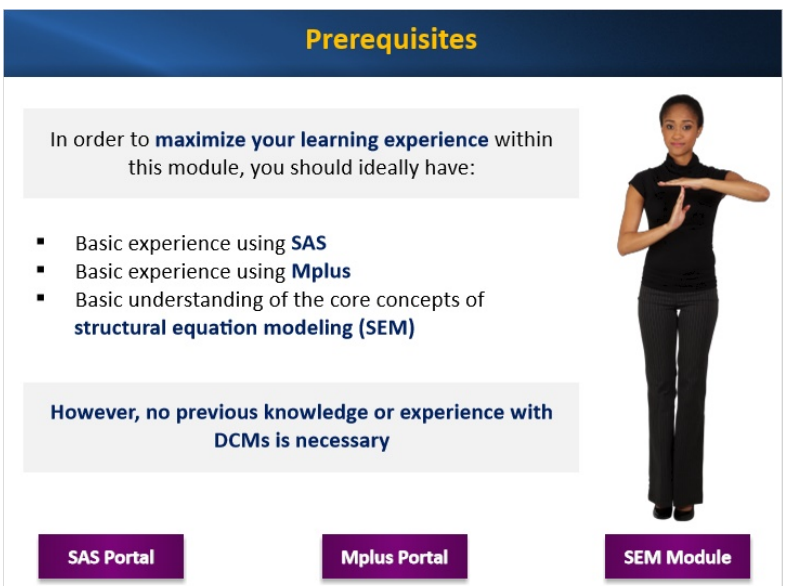
1.12 Scope (II)



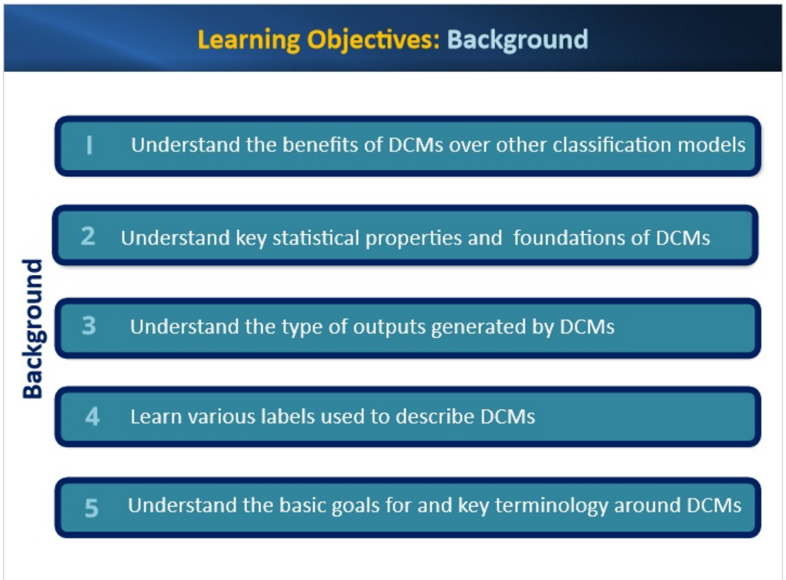
1.13 Scope (III)



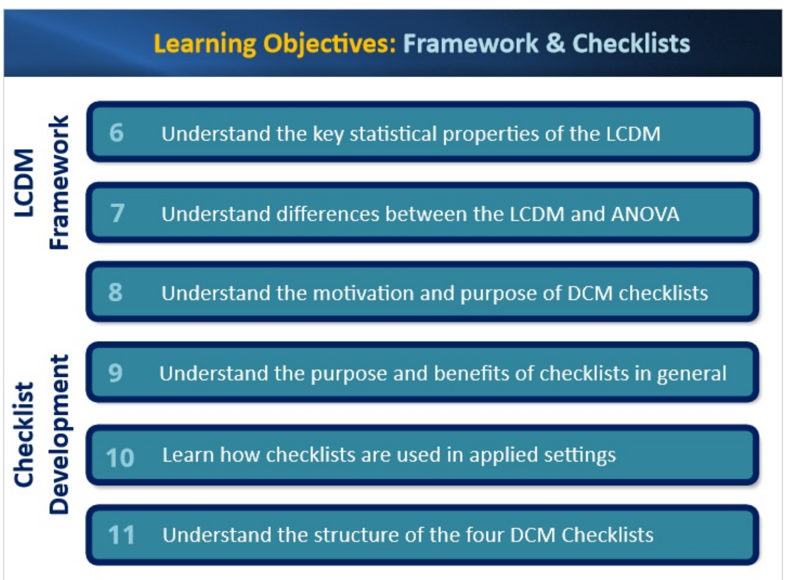
1.14 Prerequisites



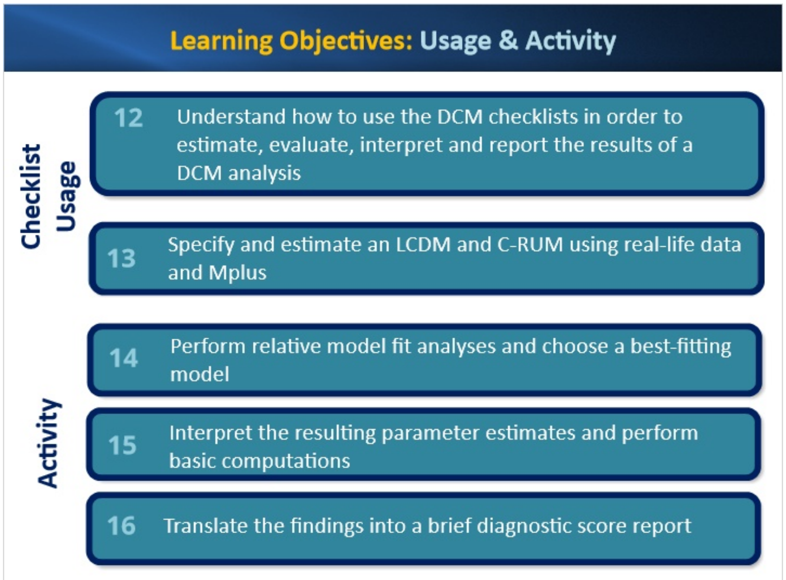
1.15 Objectives (I)



1.16 Objectives (II)

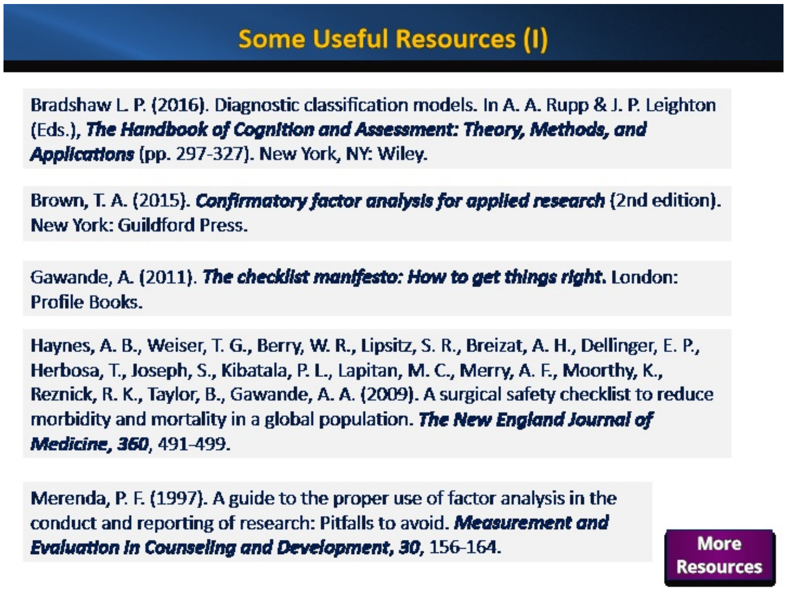


1.17 Objectives (III)

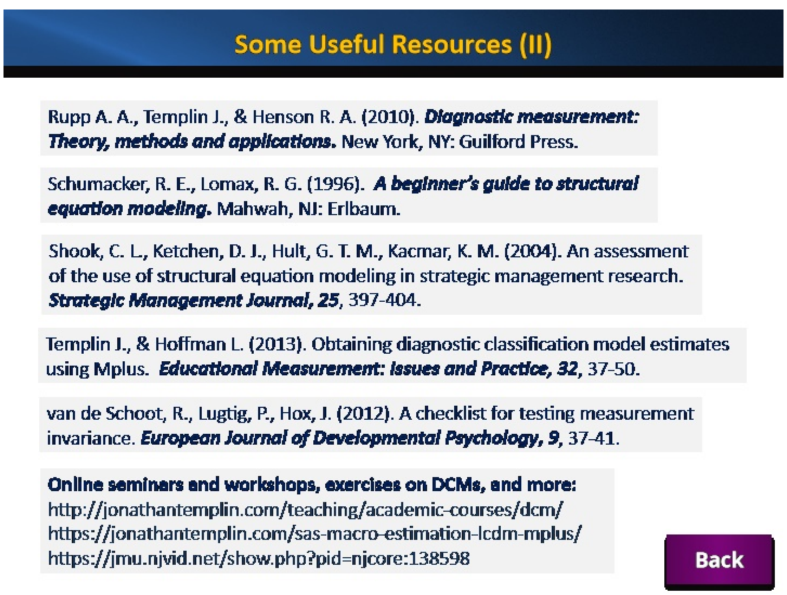


1.18 Resources

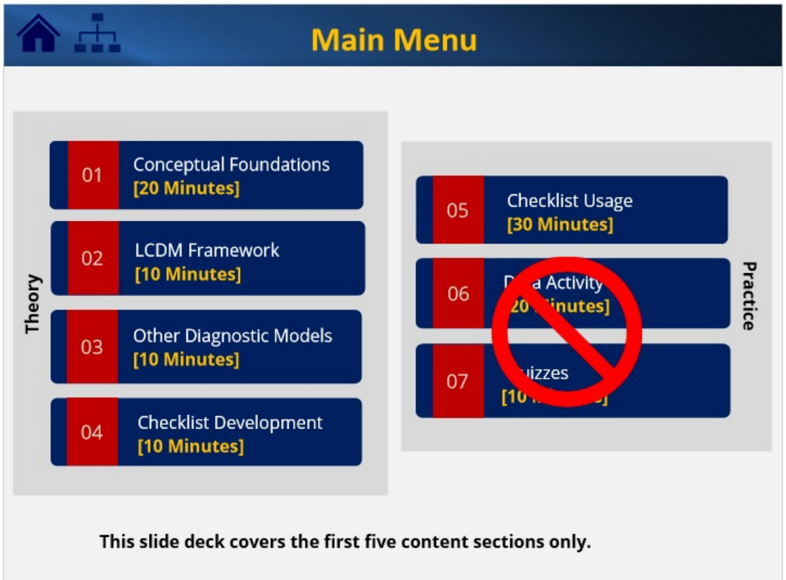
References (I) (Slide Layer)



References (II) (Slide Layer)



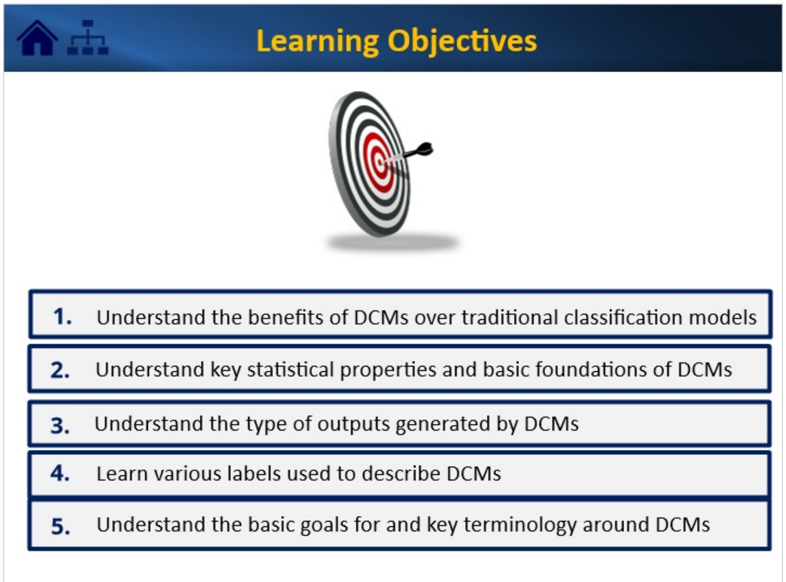
1.19 Main Menu



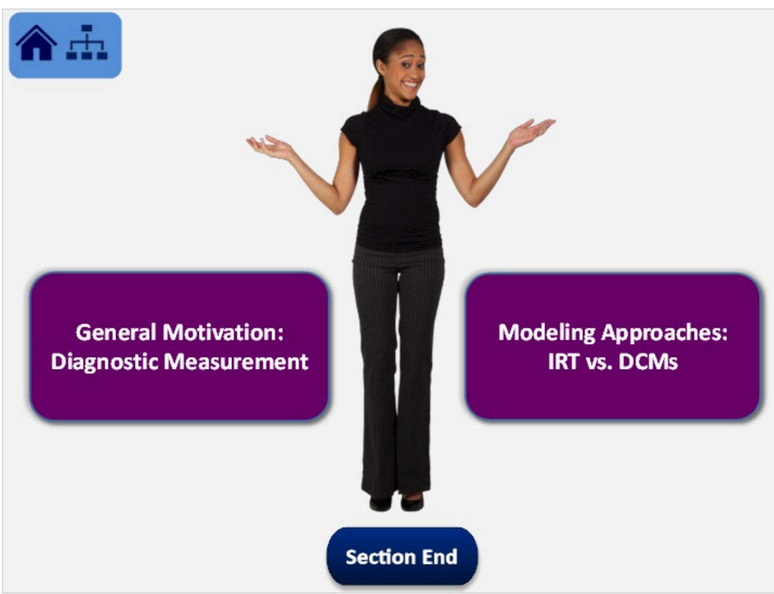
2. Section 1: Conceptual Foundations

2.1 Cover: Section 1

2.2 Learning Objectives: Section 1

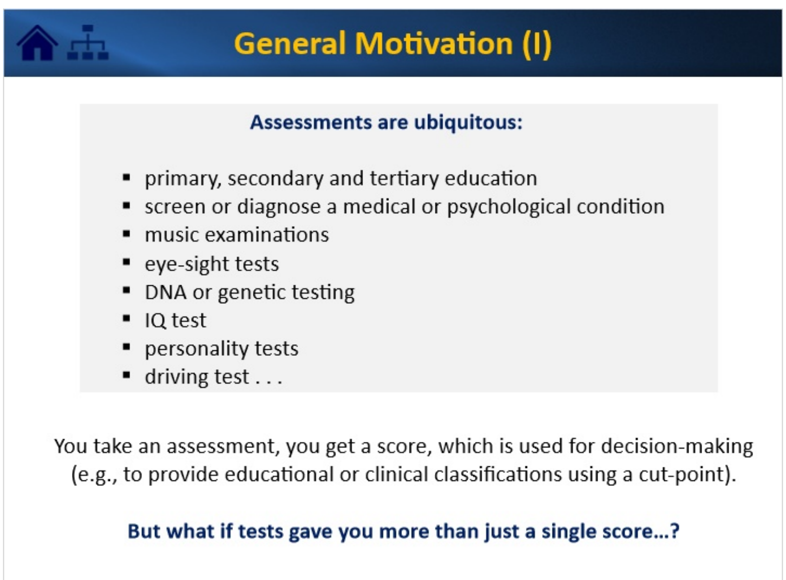


2.3 Topic Selection

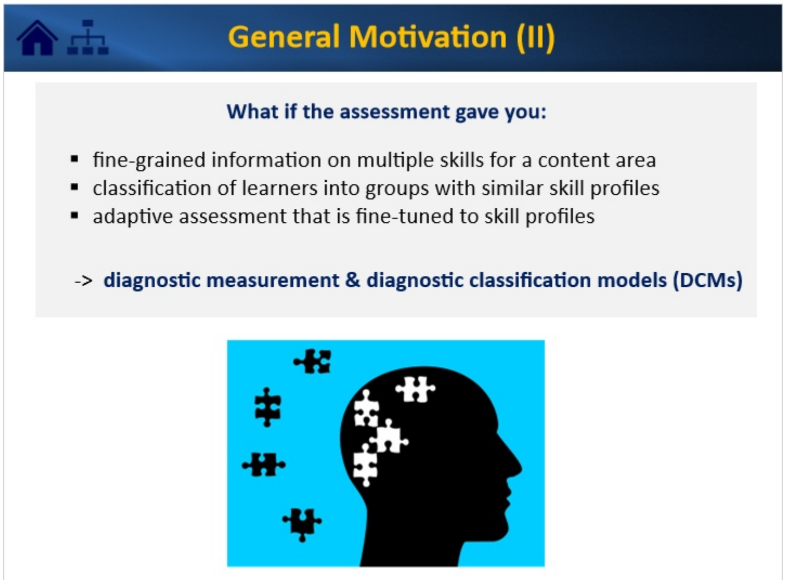


2.4 Bookmark: General Motivation

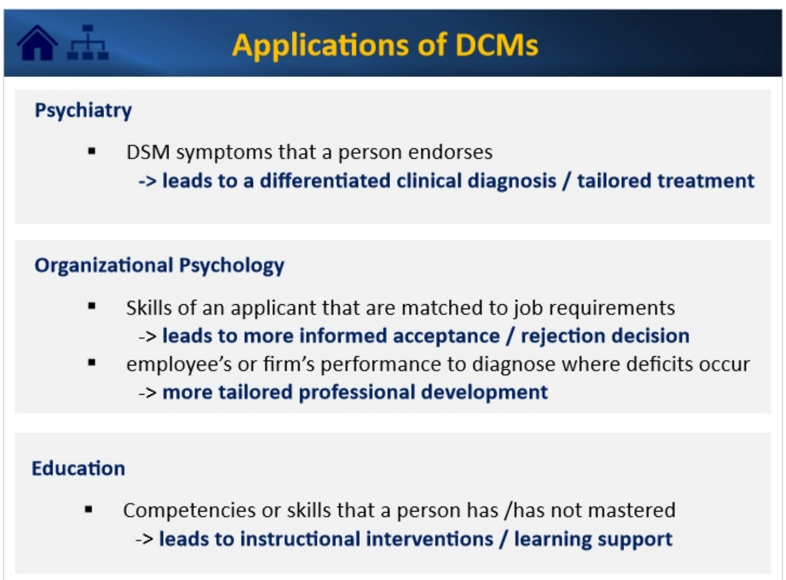
2.5 General Motivation (I)



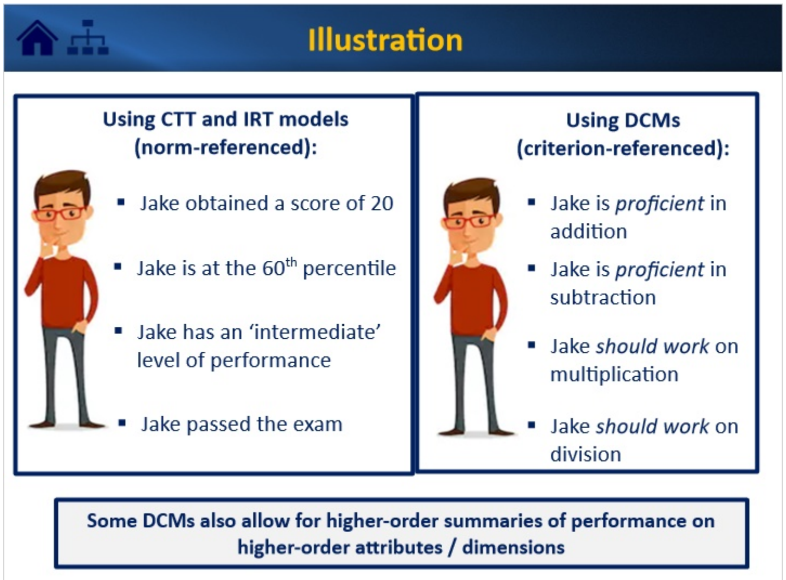
2.6 General Motivation (II)



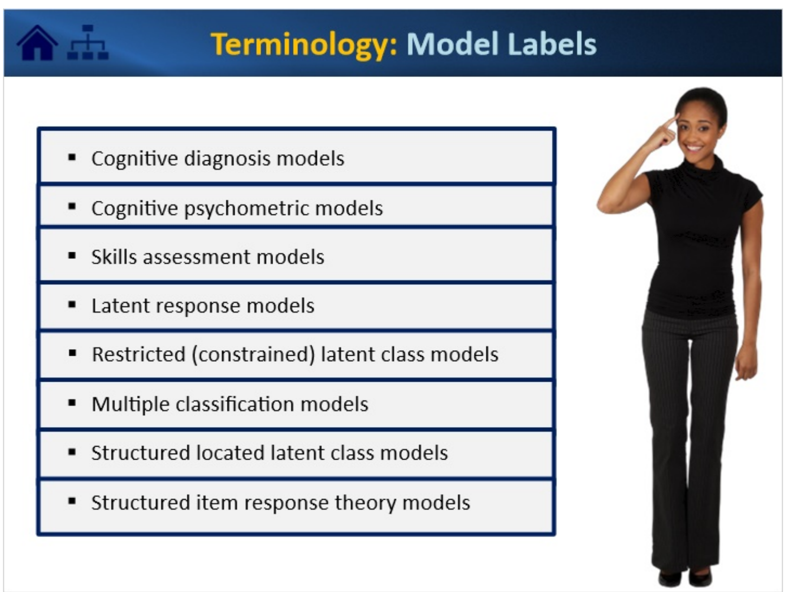
2.7 Applications of DCMs



2.8 Illustration



2.9 Terminology: Model Labels



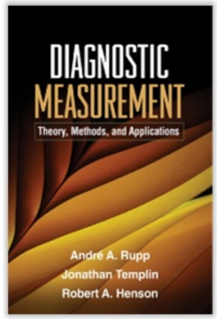
2.10 Terminology (II)

Terminology: Resources

The next slide provides some **basic terminology** for the ITEMS module

Additional terms are explained in the **'Glossary'** section of the player interface for this ITEMS module

An **extensive glossary** is also provided in the book '*Diagnostic Measurement: Theory, Methods, and Applications*'



2.11 Basic Terminology

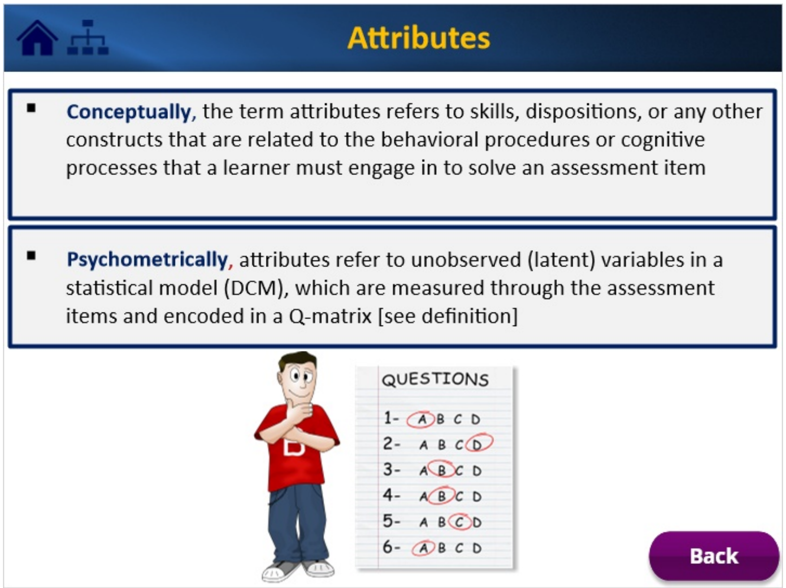
Terminology: Mini Glossary

Term	Conceptually	Psychometrically
Attribute	Unobservable features	Statistical variable
Diagnosis	Clinical evaluation	Statistical classification
Dimension	Construct aspect	Statistical variable
Item	Stimulus	Statistical variable
Latent variable	Dimension	Statistical variable
Latent class	Group of learners	Set of observations
Q-matrix	Design mapping	Matrix with numbers

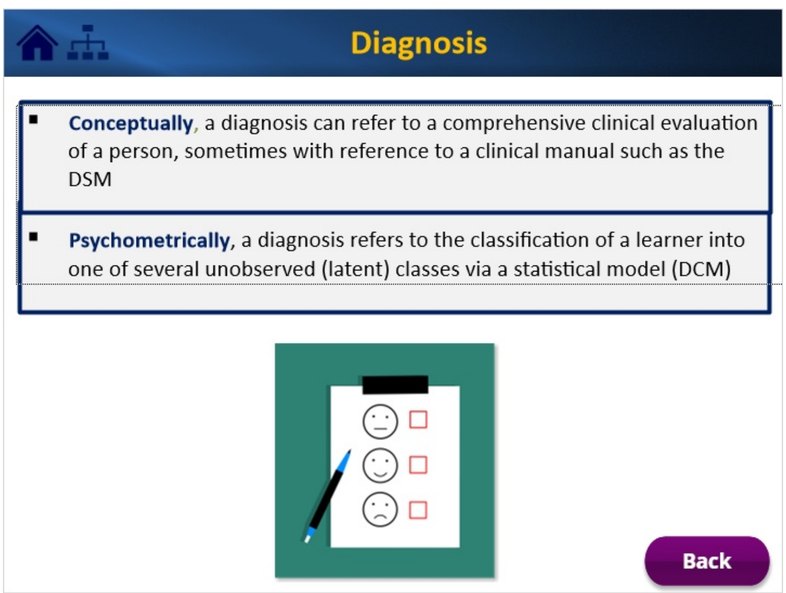
Click on each row to see an additional explanation.

Part End

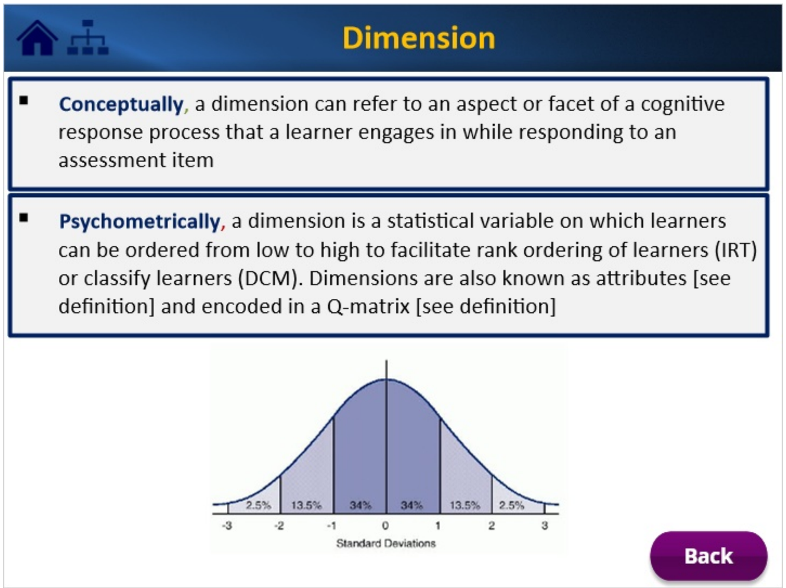
2.12 Attribute



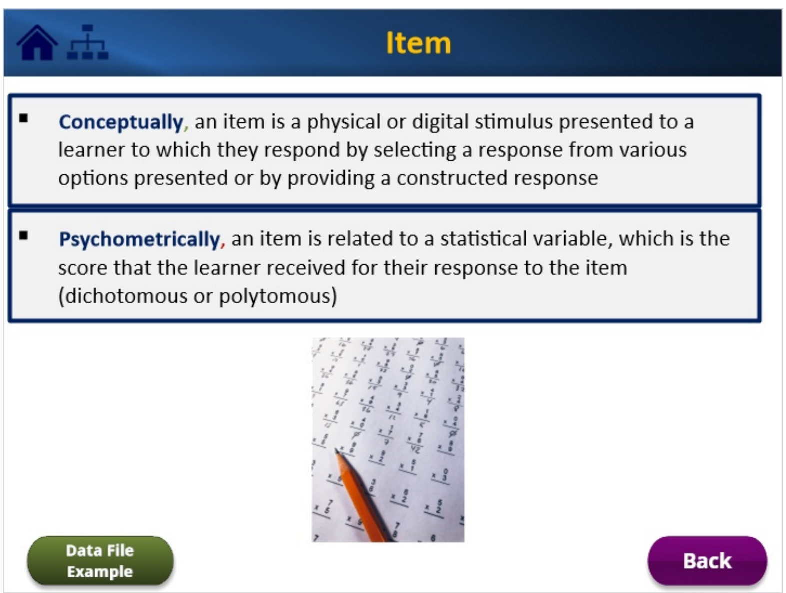
2.13 Diagnosis



2.14 Dimension



2.15 Item



2.16 Data File: Example

Data File: Example

Columns = Items

Rows = Individuals

	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
Individual 1	1	0	1	0	1	1
Individual 2	1	0	0	0	0	0
Individual 3	0	1	1	1	0	1
Individual 4	1	0	0	1	0	0
Individual 5	1	0	0	0	0	0
Individual 6	0	1	1	1	0	1
Individual 7	1	0	1	0	1	0
Individual 8	1	0	0	1	0	1

Cells = Observed Item Response
(0 = incorrect / not endorsed, 1 = correct / endorsed)

2.17 Latent Variable

Latent Variable

- **Conceptually**, a latent variable is a dimension along which we compare learners whose meaning is anchored in our definition of the construct that the assessment is measuring

- **Psychometrically**, a latent variable is an unobserved statistical quantity that we estimate using the observed scores from learners along with the associated item parameters for the assessment items

Back

2.18 Latent Class

Latent Class

- **Conceptually**, a latent class is an unobserved grouping of learners that share similar characteristics – in the case of DCMs, this is the same set of attribute mastery statues / attribute profiles

- **Psychometrically**, a latent class is an unobserved classification state into which learners are sorted by estimating model parameters. The number of latent classes is pre-determined by the number of attributes and the number of mastery levels. The latent classes are mutually exclusive

Back

2.19 Q-matrix

Q-matrix

- **Conceptually**, a Q-matrix shows the association between items and dimensions for an assessment or indicates which items provide measurement information about which dimensions

- **Psychometrically**, a Q-matrix is a two-dimensional table (rows represent items, columns represent attributes) with numeric entries (typically 0s and 1s) that is used to compute the response probabilities for individual items and latent classes under a given DCM

	Attribute 1	Attribute 2	Attribute 3
Item 1	0	1	0
Item 2	1	0	0
Item 3	1	1	0
Item 4	0	1	1

Q-matrix Example

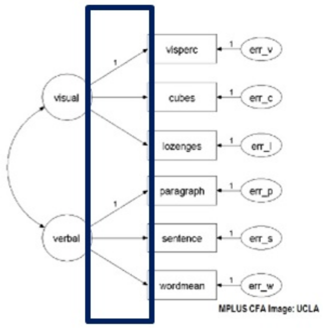
Back

2.20 Qmatrix: Item-attribute Alignment

Q-matrix: Item-attribute Alignment

- A Q-matrix is a central feature of DCMs and **specified a priori** to indicate which latent attributes are measured by each item (i.e., **item-attribute alignment**)

- A Q-matrix is identical to the **factor pattern matrix in a confirmatory factor analysis**



2.21 Q-matrix: Example

Q-matrix: Example

Item	Attribute 1	Attribute 2	Highest level of interaction
1	1	0	1
2	1	1	2
3	0	1	1
4	1	0	1
5	1	0	1
6	1	0	1
7	1	0	1
8	1	0	1
9	1	1	2
10	1	0	1
11	1	1	2
12	1	1	2
13	1	1	2

Attribute columns: 1 = attribute is measured, **0** = attribute is not measured

Level of interaction: 1 = main effect, **2** = 2-way interaction

2.22 Q-matrix: Specification

Q-matrix: Specification

- The specification of a Q-matrix **underlies all inferences** resulting from a DCM analysis. Therefore, accurate specification of the Q-matrix is **critical as it affects model fit and interpretation**

- In education, the initial specification of a **Q-matrix typically requires content-specific learning theory and expert insights** from teachers, researchers and psychometricians

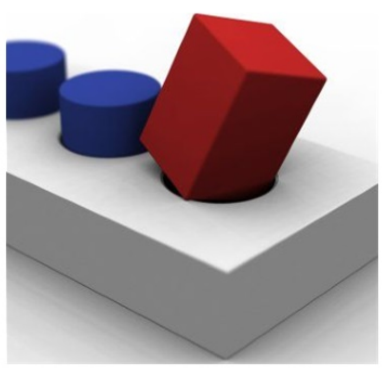
- Verifying the **item-attribute alignment** is a complex process that requires **substantial qualitative research** to identify the specific mental processes that examinees use to respond to items

2.23 Q-matrix: Retrofitting

Q-matrix: Retrofitting

- Since **large-scale applications** of DCMs are still in their infancy, there are **few studies** that have **prospectively created tests** designed to be modeled with a DCM

- Consequently, **most studies** unfortunately use **retrofitted** data from assessments that were **not originally designed** for analyses with DCMs



2.24 Bookmark: Modeling Approaches

2.25 Overview

Overview

Multidimensional IRT	DCMs
Multiple continuous variables	Multiple discrete variables
Continuous score profiles	Classifications into latent classes
Item difficulty and discrimination	Item guessing and slipping
Parametric estimation	Parametric estimation
Fit assessment possible	Fit assessment possible
Score reliability / precision	Classification reliability
Monotonicity	Partial monotonicity

2.26 IRT Foundations (I)

IRT Foundations (I)

- Performance is based on a **single continuous latent trait** θ ***(unidimensional IRT)*** or **multiple continuous latent traits** $\underline{\boldsymbol{\theta}}$ **(trait vector)** ***(multidimensional IRT)***

- Students with **higher** latent trait values have **higher** probabilities of getting an **item correct** ***(dichotomous items)*** or obtaining a **higher score** ***(polytomous items)***

2.27 IRT Foundations (II)

IRT Foundations (II)

- **Item parameters** can be used to characterize an item's operating characteristics such as difficulty, discrimination, or guessing ***(number of parameters depends on model)***

- **Score precision / item information** and **reliability estimates** can be computed for each latent variable ***(via information functions and marginal statistics)***

2.28 DCM Foundations (I)

DCM Foundations (I)

- DCMs are a family of **parametric psychometric models** that:
  - ✓ **classify respondents** into mutually exclusive classes
  - ✓ **provide fine-grained feedback** on performance via a multidimensional profile of latent skills based on responses to a set of items

- DCMs are **constrained versions of latent class models** where the number of classes is specified **a priori *(like confirmatory factor analysis)***

2.29 DCM Foundations (I)

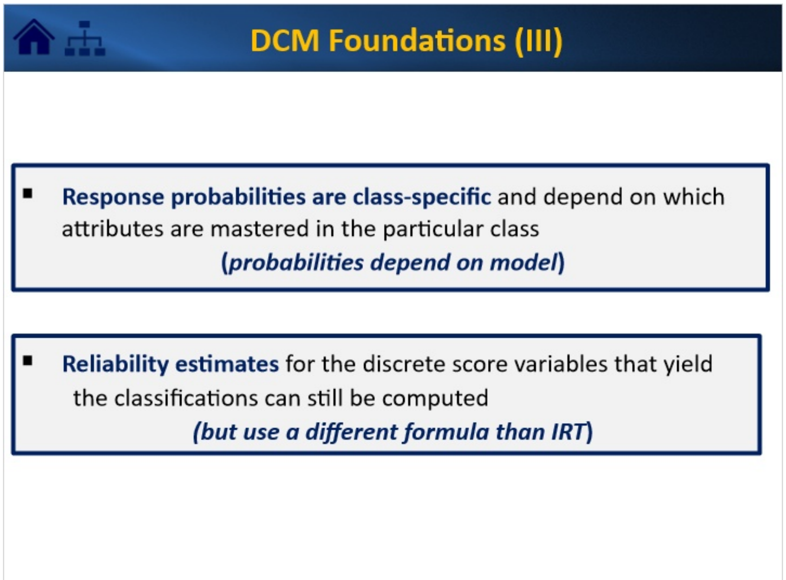
DCM Foundations (II)

- Performance is based on **multiple discrete latent variables**, which are also called attributes $\boldsymbol{\alpha} = (\alpha_1,\ldots,\alpha_K)$
  (*similar to multidimensional IRT*)

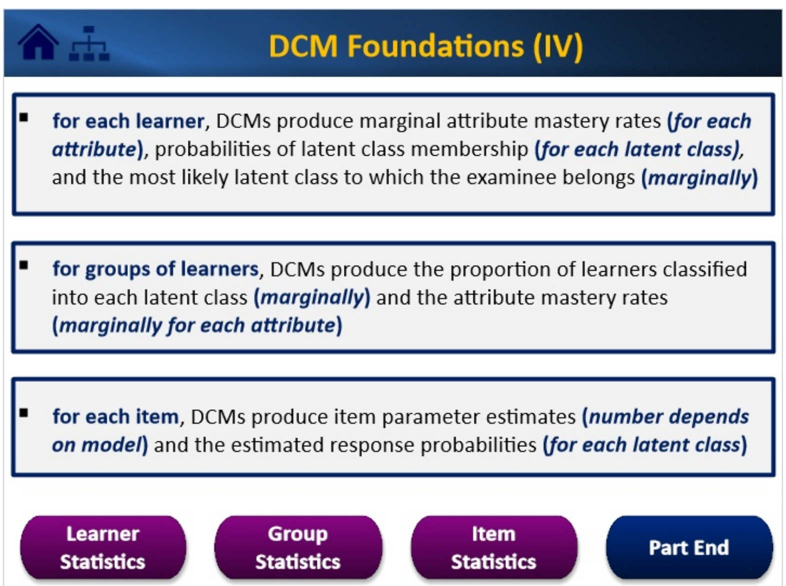
- The discrete variables result in a **multi-faceted classification** of learners organized into latent classes
  (*unlike multidimensional IRT*)

- Each item is designed to measure one or more latent attributes with the exact design captured in a **Q-matrix with 0s and 1s**
  (*similar to confirmatory factor analysis*)

2.30 DCM Foundations (III)



2.31 DCM Foundations (IV)



2.32 Learner Statistics: Probilities

Learner Statistics: Probabilities

Below is an extract of results from an LCDM based on 13 items, 2 attributes and 4 latent classes. This SAS output displays the:

- ✓ **posterior probabilities** of latent class membership for each class;
- ✓ **latent class to which each respondent has been assigned** based on their highest posterior probability;
- ✓ **marginal attribute probability for** each attribute

	ID	cprob1	cprob2	cprob3	cprob4	class	prob_attribute1	prob_attribute2
1	1	0.02709	0.03823	0.31229	0.6224	4	0.93469	0.66063
2	2	0.0622	0.10936	0.24326	0.58519	4	0.82845	0.69455
3	3	0.32058	0.4524	0.07585	0.15117	2	0.22702	0.60357
4	4	0.97556	0.0216	0.0027	0.00015	1	0.00285	0.02175
5	5	0.00534	0.0144	0.31674	0.66352	4	0.98026	0.67792
6	6	0.58578	0.40042	0.00762	0.00618	1	0.0138	0.4066
7	7	0.0646	0.27956	0.15639	0.49945	4	0.65584	0.77901
8	8	0.5183	0.44144	0.02035	0.01991	1	0.04026	0.46135
9	9	0.96872	0.02764	0.0034	0.00023	1	0.00363	0.02787
10	10	0.90666	0.06655	0.02226	0.00452	1	0.02678	0.07107
11	11	0.29626	0.32435	0.14716	0.23222	2	0.37938	0.55657
12	12	0.30561	0.33459	0.13956	0.22023	2	0.35979	0.55482

2.33 Learner Statistics: Feedback

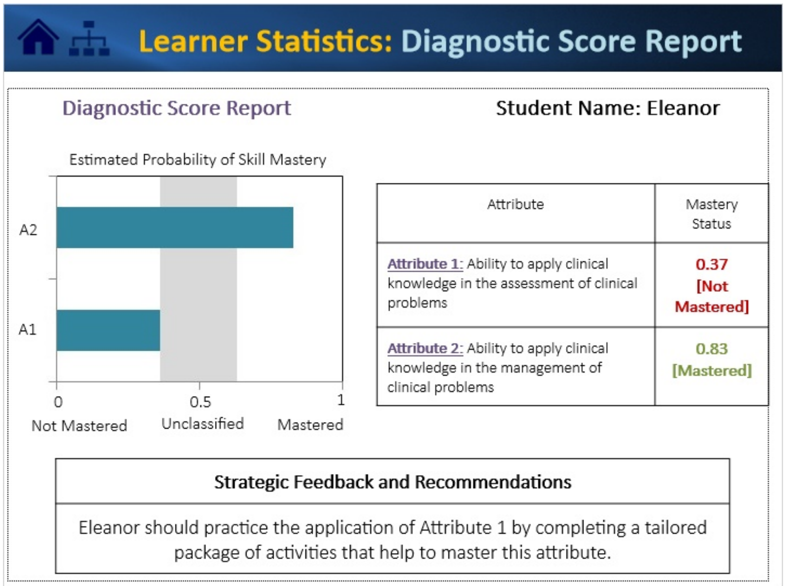
Learner Statistics: Feedback

The marginal attribute probabilities can be used to:

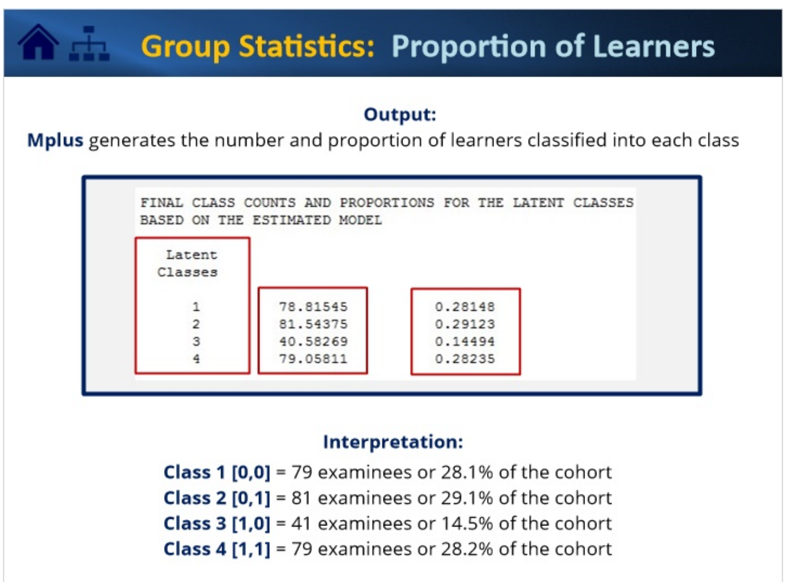
- ✓ **develop detailed diagnostic feedback for *each* respondent** to facilitate identification of remedial instruction and increase their proficiency

- ✓ **summarize the cohort's overall performance** in order to help teachers identify which components of a course they should focus on to increase overall proficiency

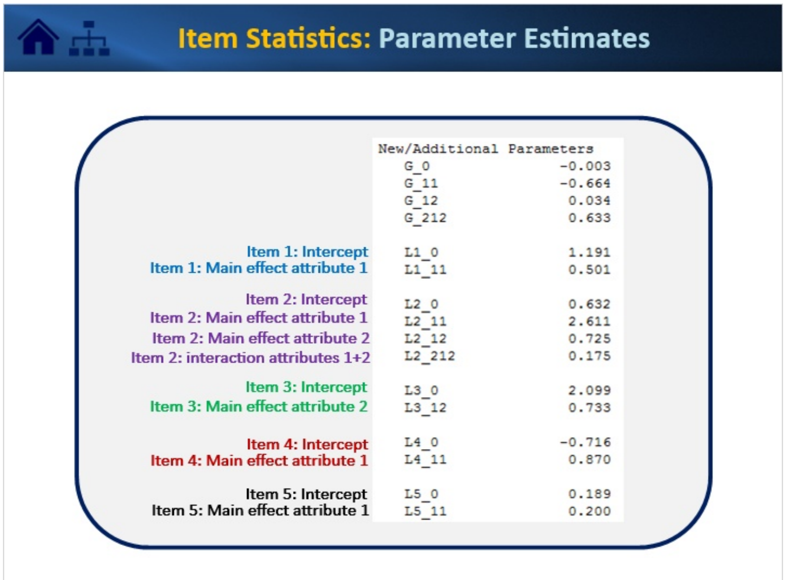
2.34 Learner Statistics: Report



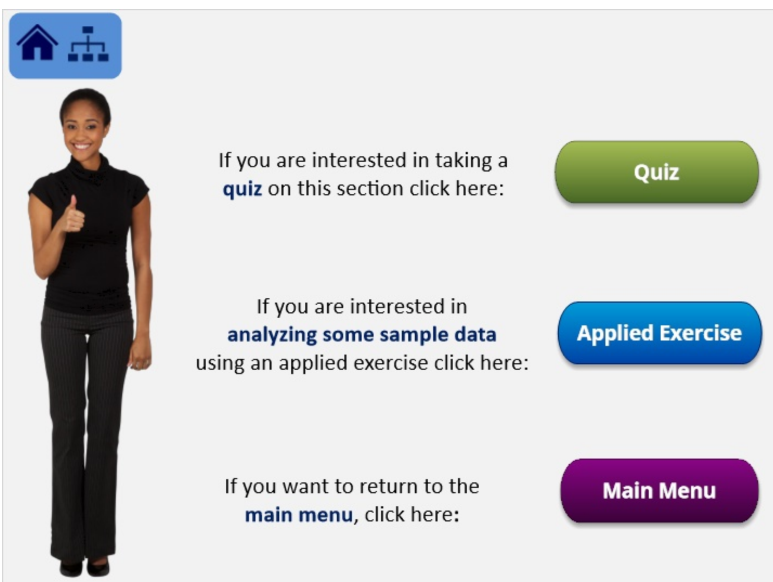
2.35 Group Statistics



2.36 Item Statistics



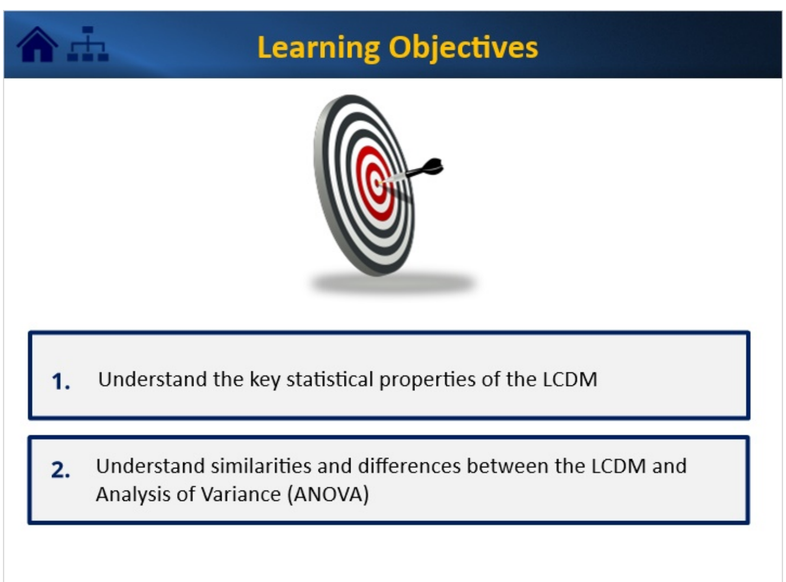
2.37 Bookend: Section 1



3. Section 2: LCDM Framework

3.1 Cover: Section 2

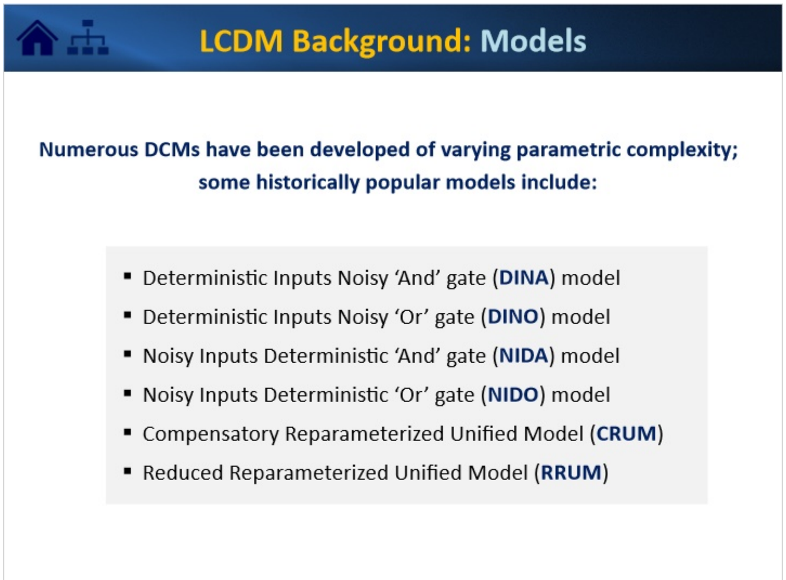
3.2 Learning Objectives: Section 2



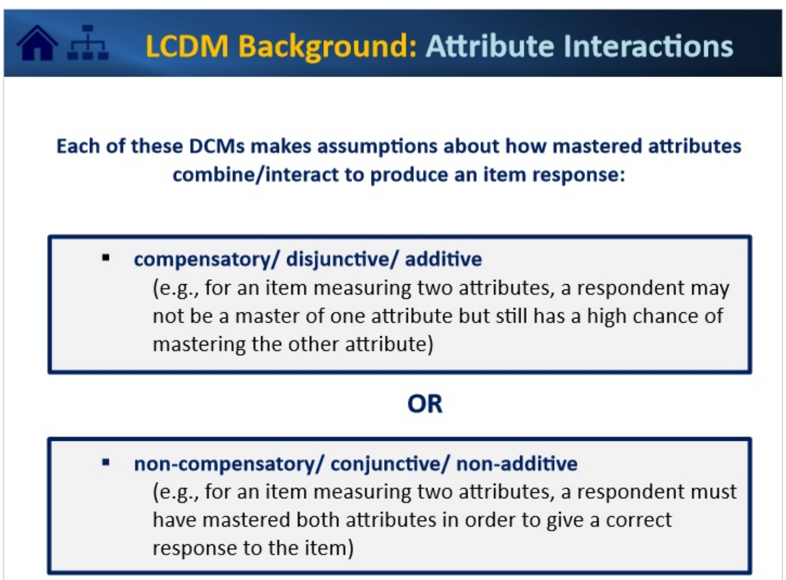
3.3 Topic Selection

3.4 Bookmark: LCDM Foundations

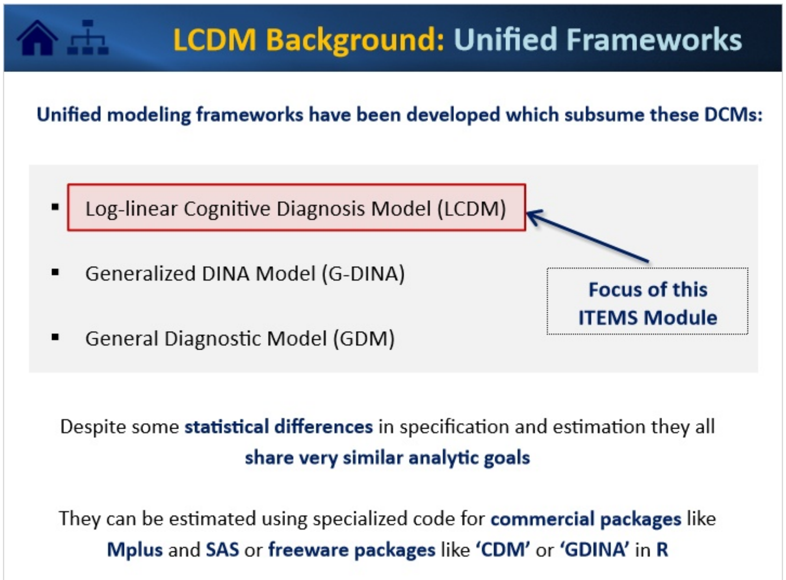
3.5 LCDM Background: Models



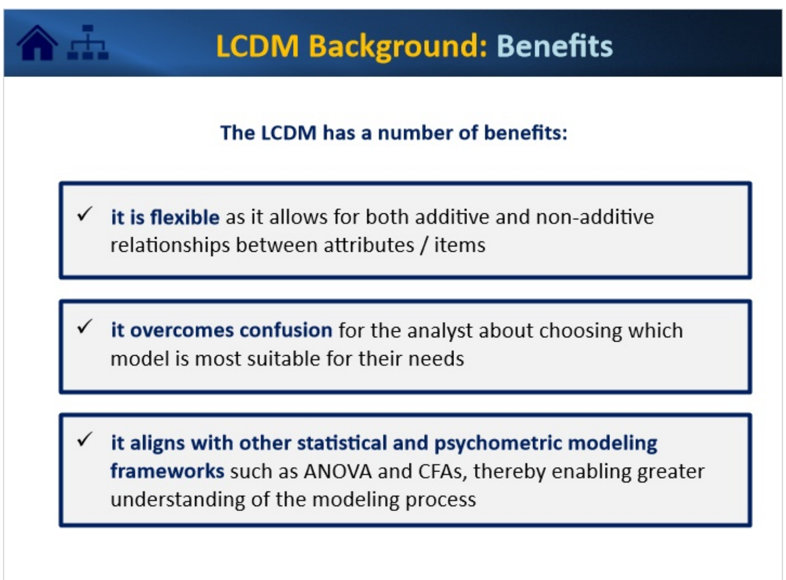
3.6 LCDM Background: Attribute Interactions



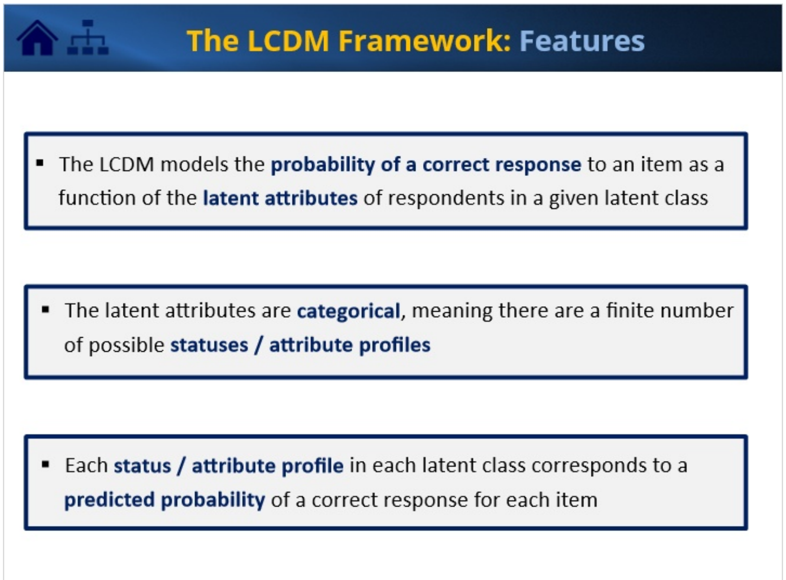
3.7 LCDM Background: Unified Frameworks



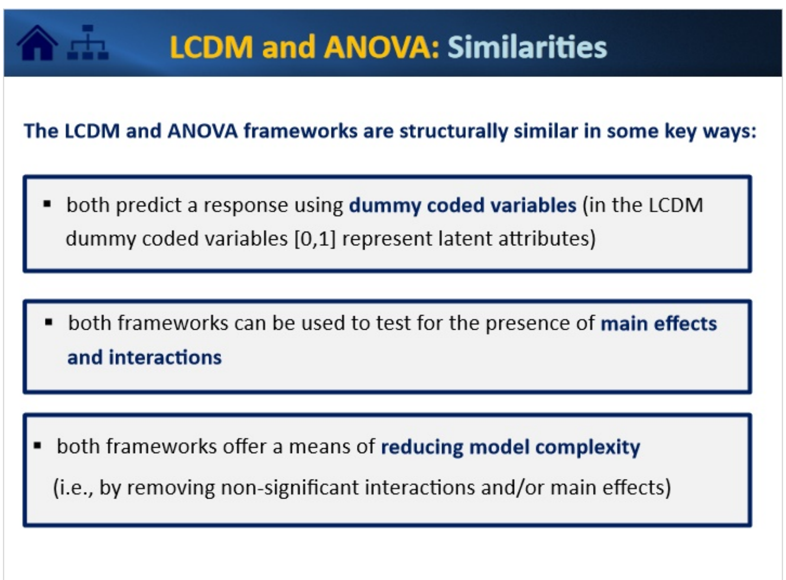
3.8 LCDM Background: Benefits



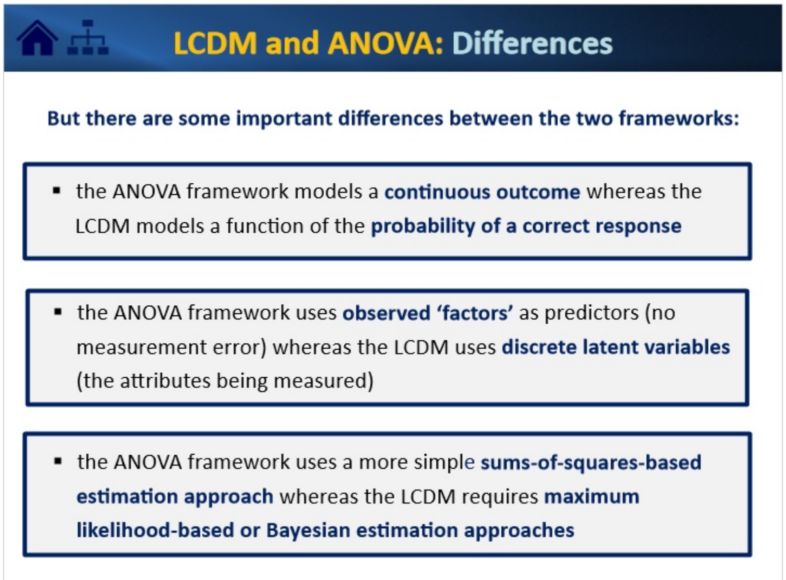
3.9 LCDM Background (V)



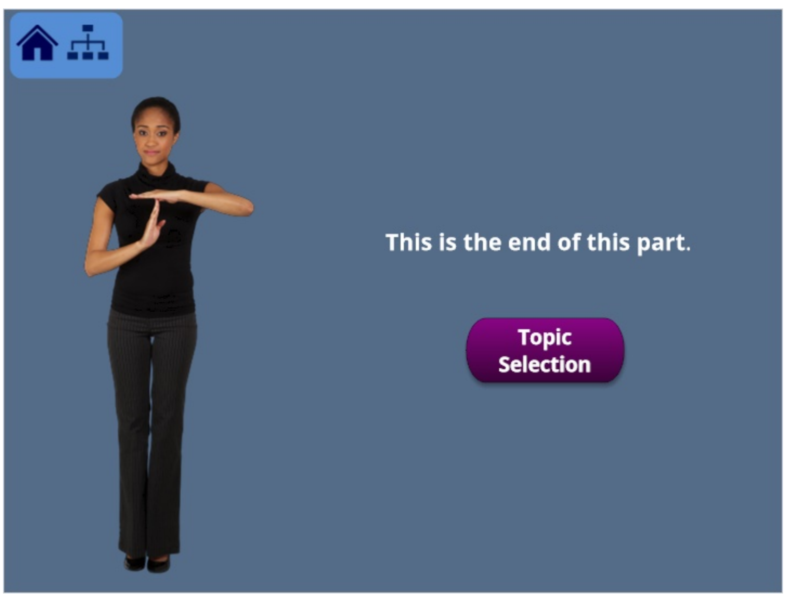
3.10 LCDM vs ANOVA (I)



3.11 LCDM vs ANOVA (II)

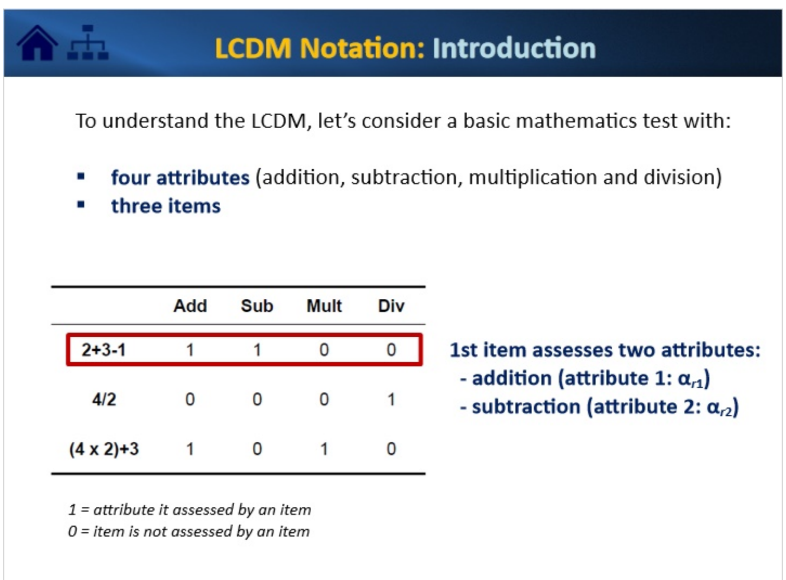


3.12 Bookend: LCDM Foundations

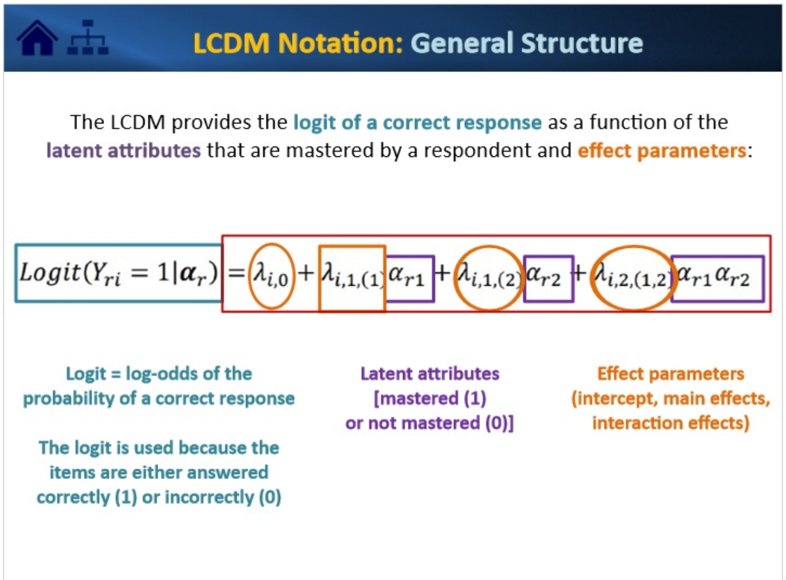


3.13 Bookmark: LCDM Estimation

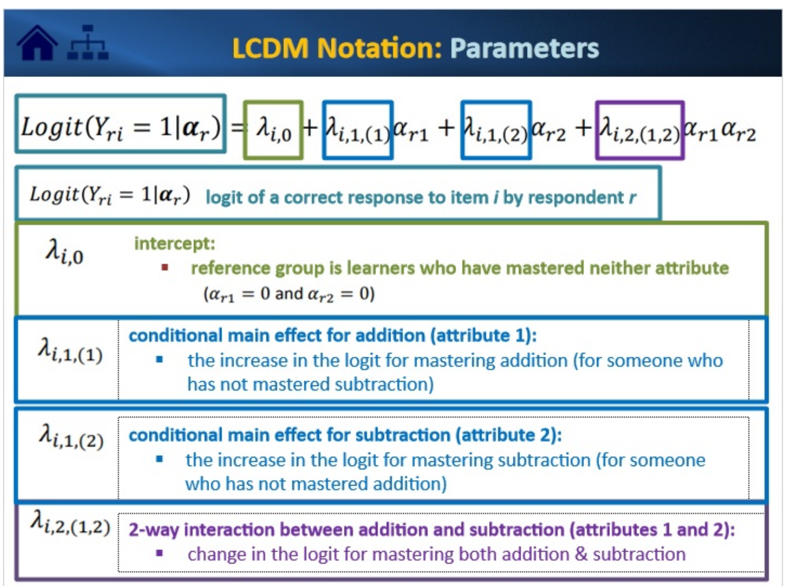
3.14 LCDM Notation: Introduction



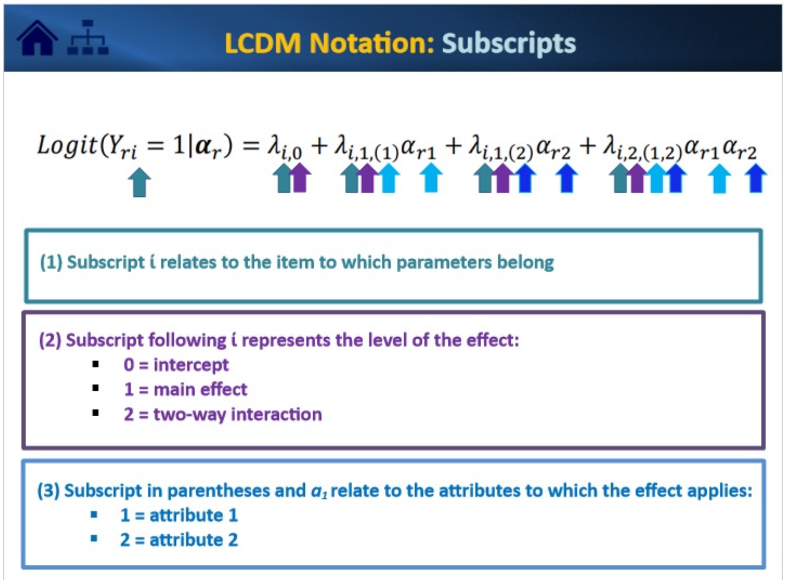
3.15 LCDM Notation: Structure



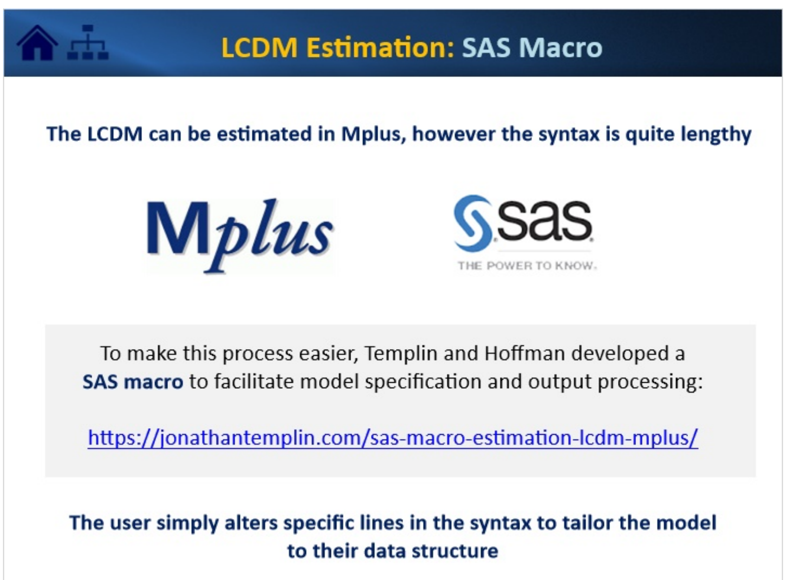
3.16 LCDM Notation: Parameters



3.17 LCDM Notation: Subscripts

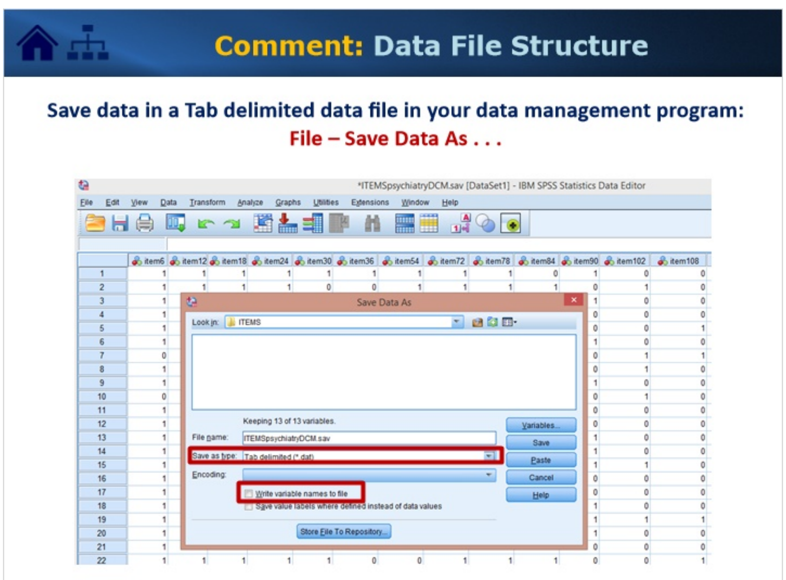


3.18 LCDM Estimtation: SAS Macro

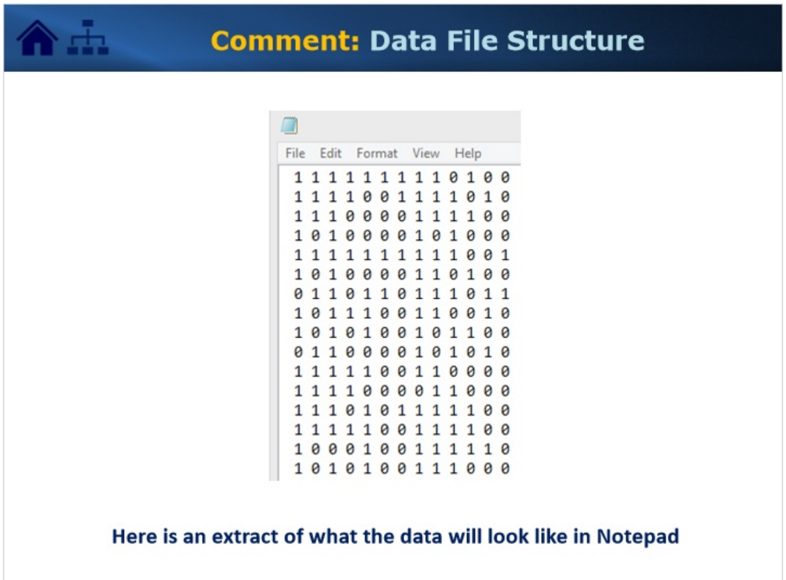


3.19 LCDM Estimation: Video

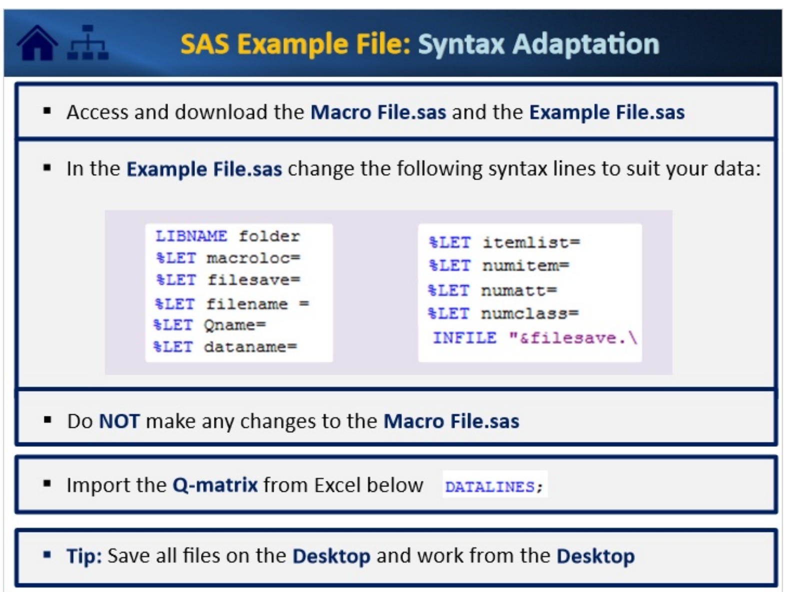
3.20 LCDM Estimation: Saving Data



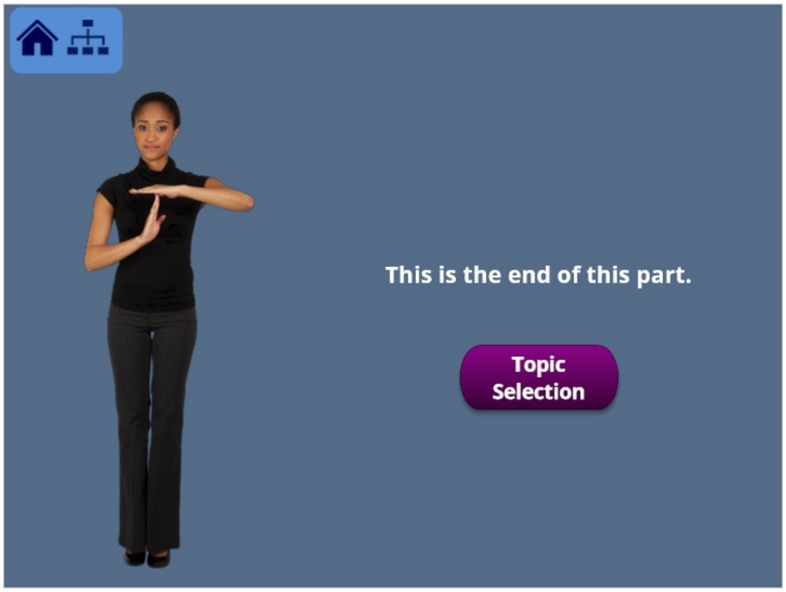
3.21 LCDM Estimation: Data File



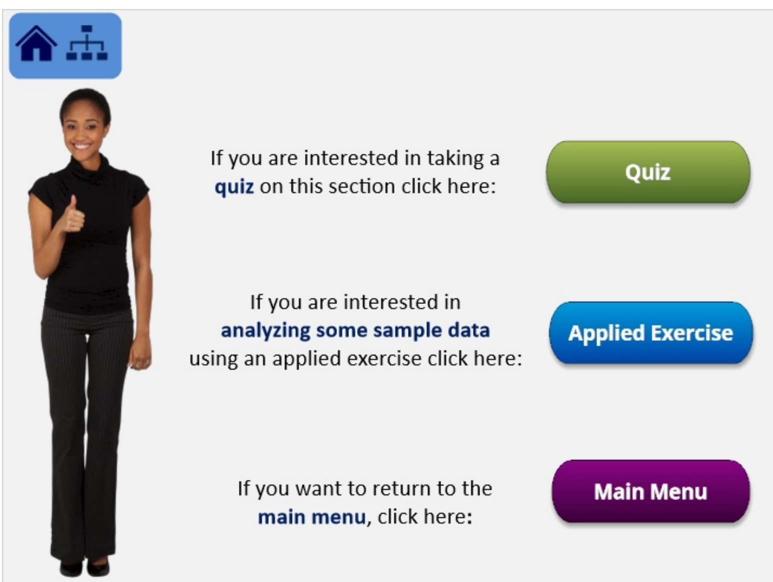
3.22 LCDM Estimation: Syntax Adaptation



3.23 Bookend: LCDM Estimation



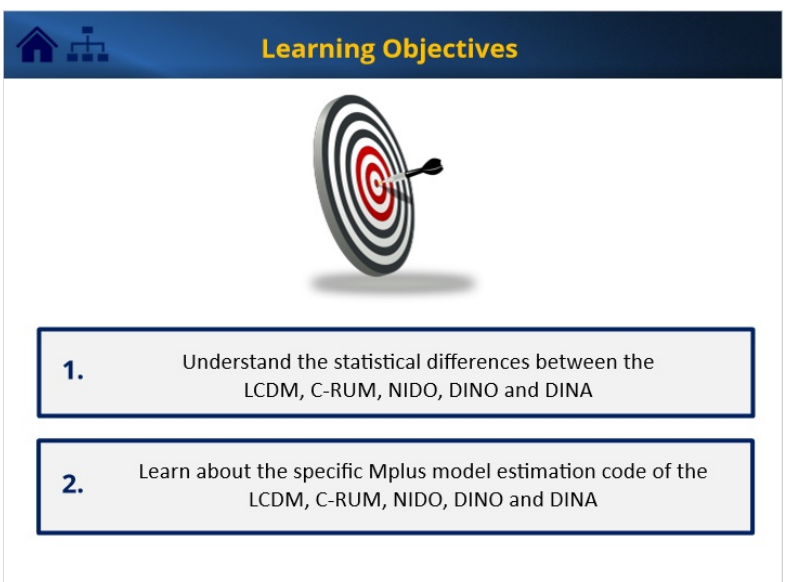
3.24 Bookend: Section 2



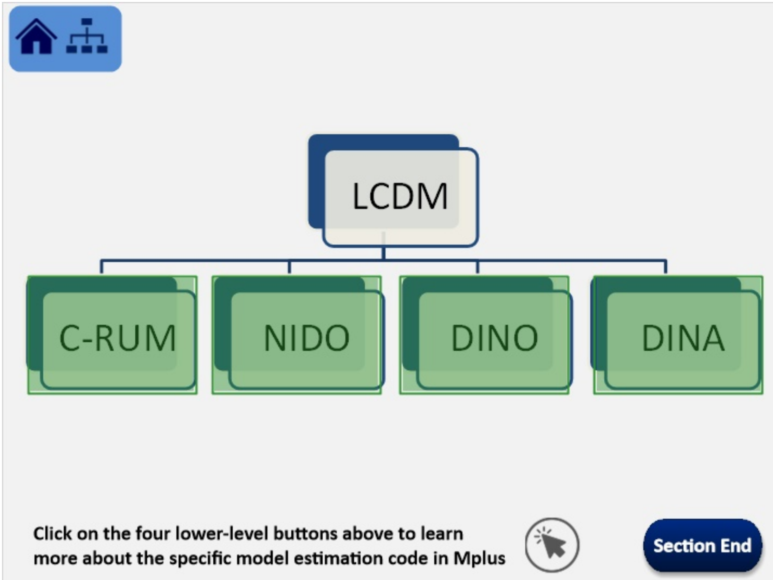
4. Section 3: Other Diagnostic Models

4.1 Cover: Section 3

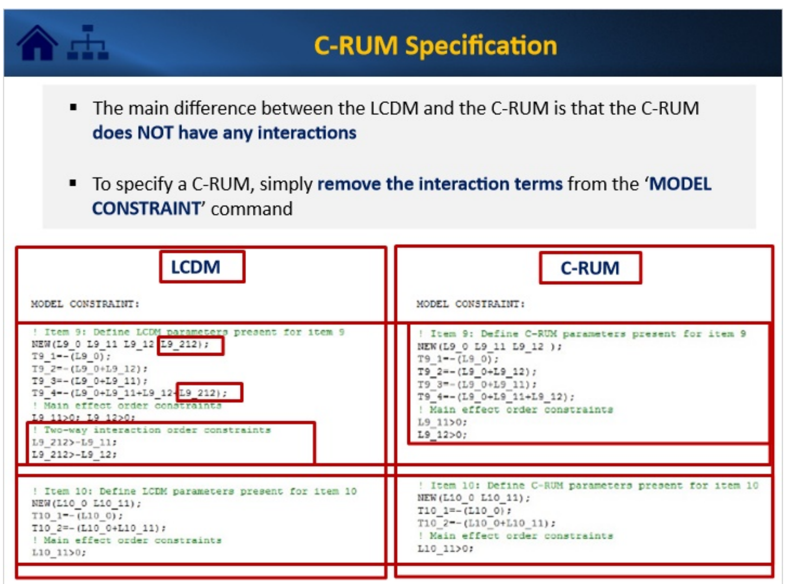
4.2 Objectives: Section 3



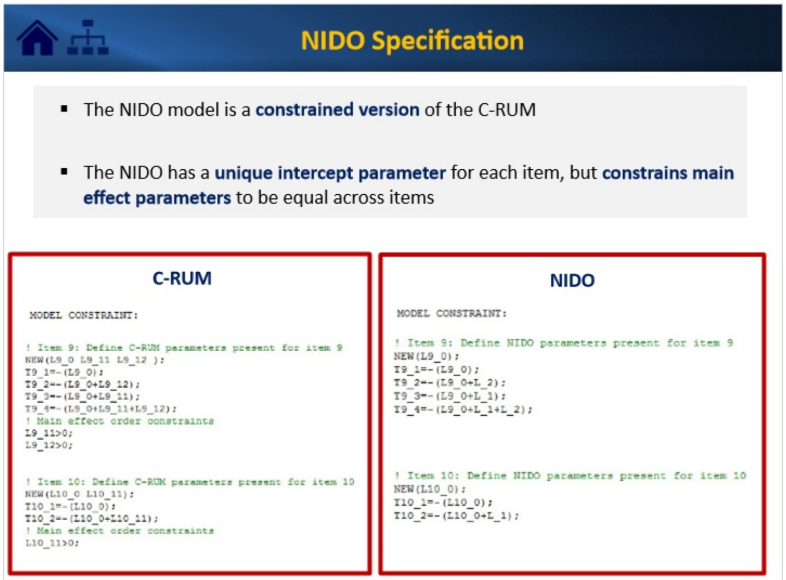
4.3 Model Selection



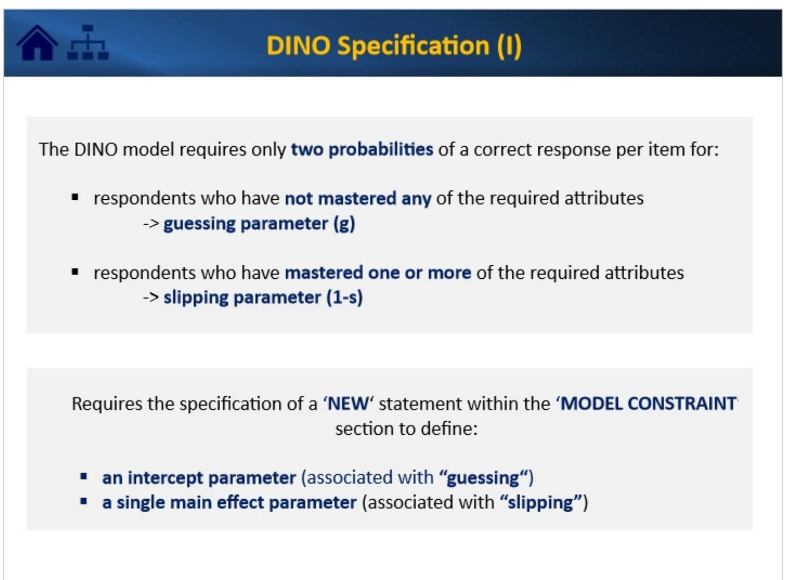
4.4 C-RUM Specification (Mplus)



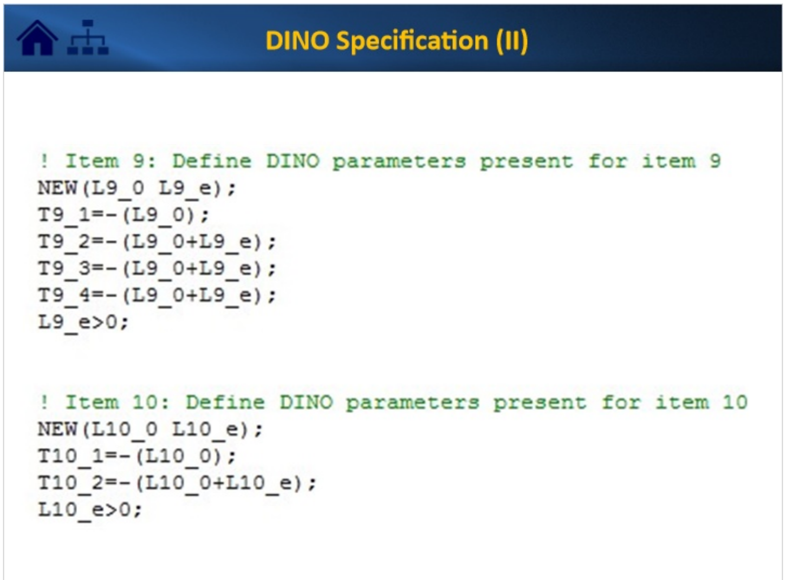
4.5 NIDO Specification (Mplus)



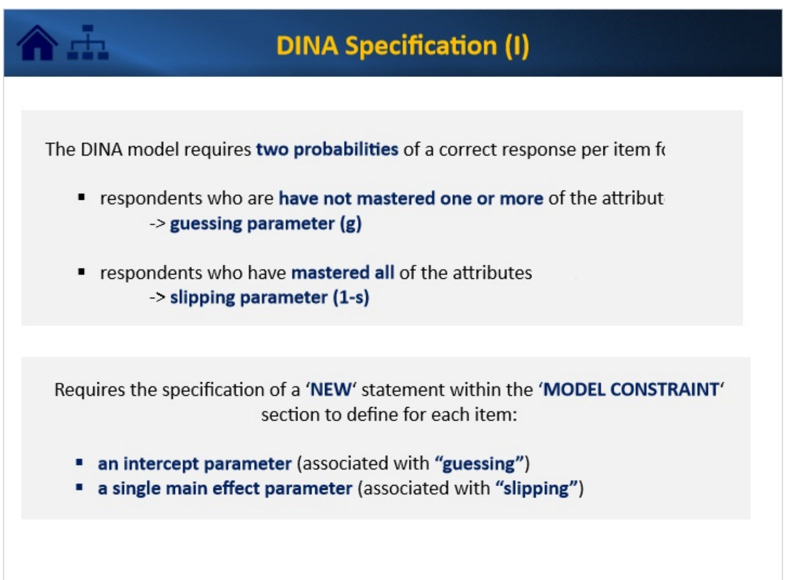
4.6 DINO Specification I (Mplus)



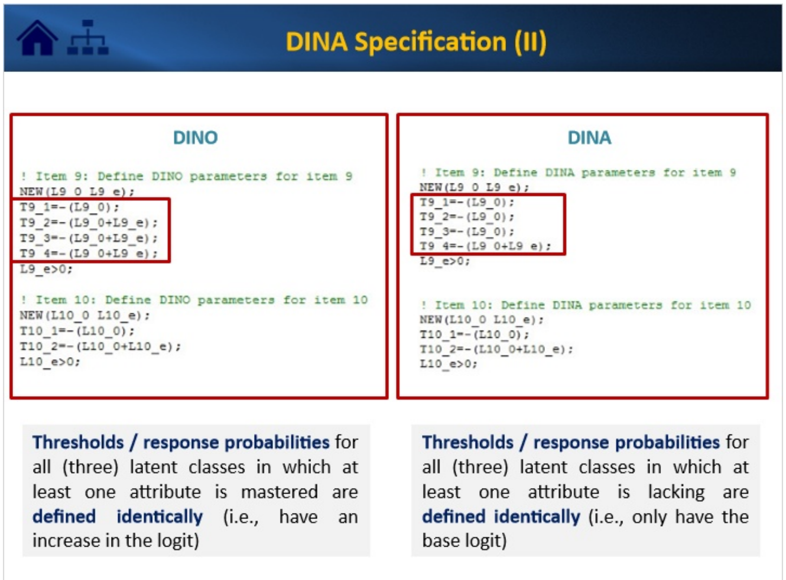
4.7 DINO Specification II (Mplus)



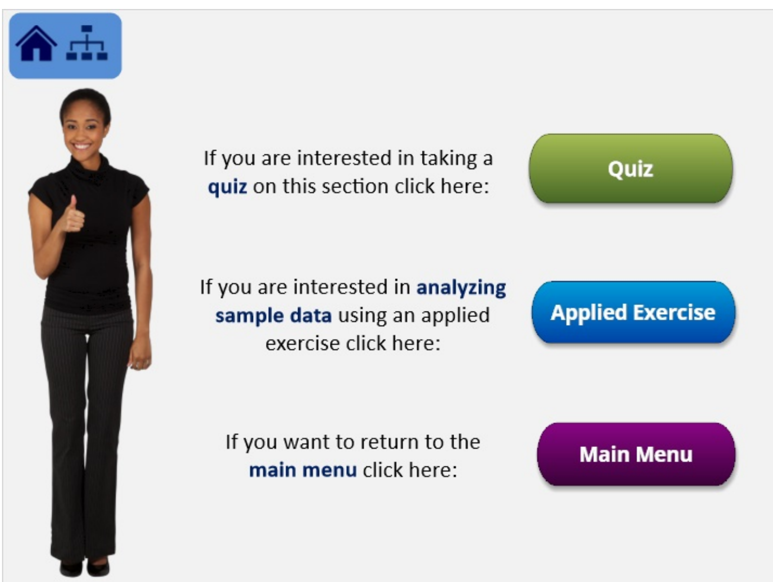
4.8 DINA Specification I (Mplus)



4.9 DINA Specification II (Mplus)

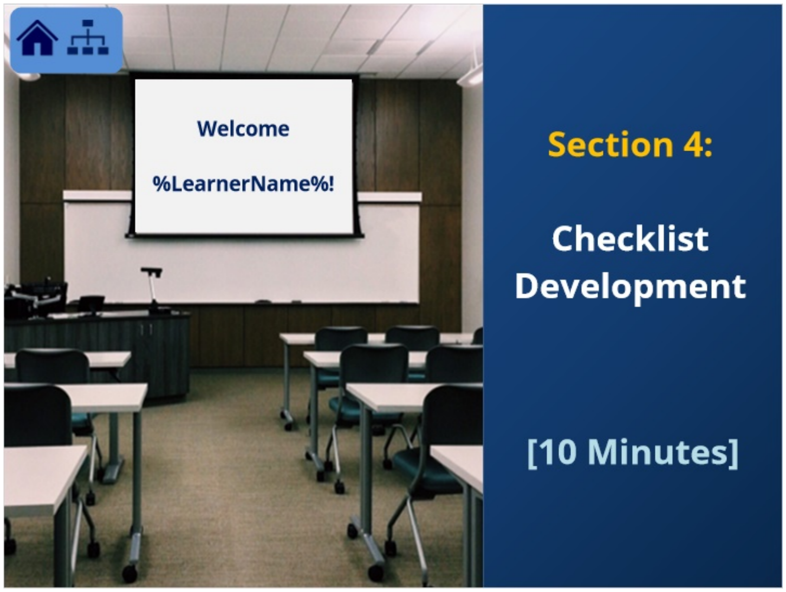


4.10 Bookend: Section 3

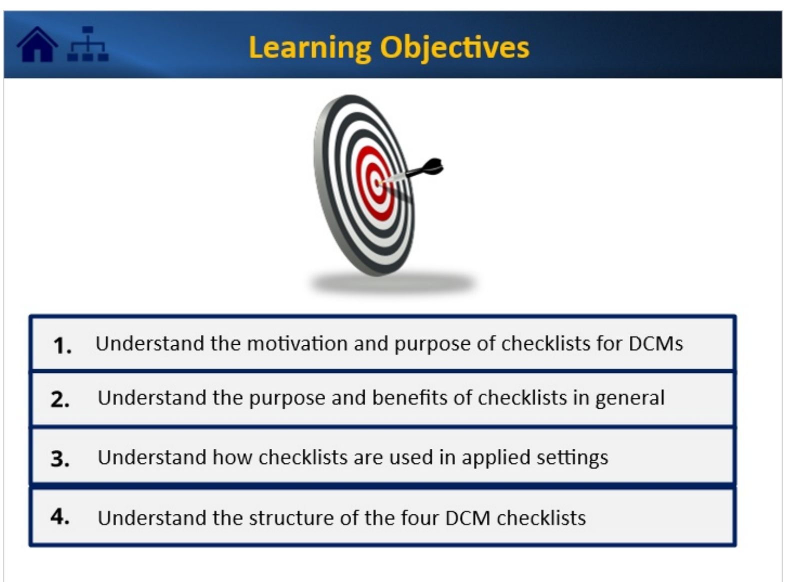


5. Section 4: Checklist Development

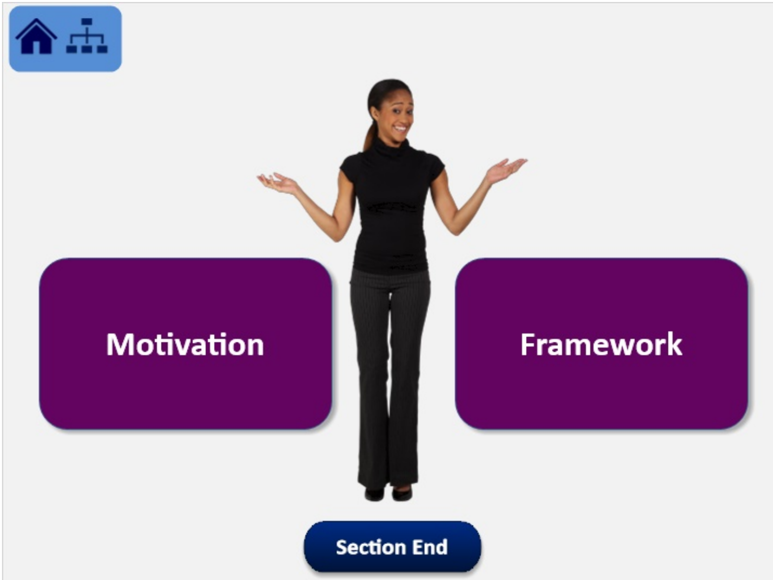
5.1 Cover: Section 4



5.2 Learning Objectives: Section 4

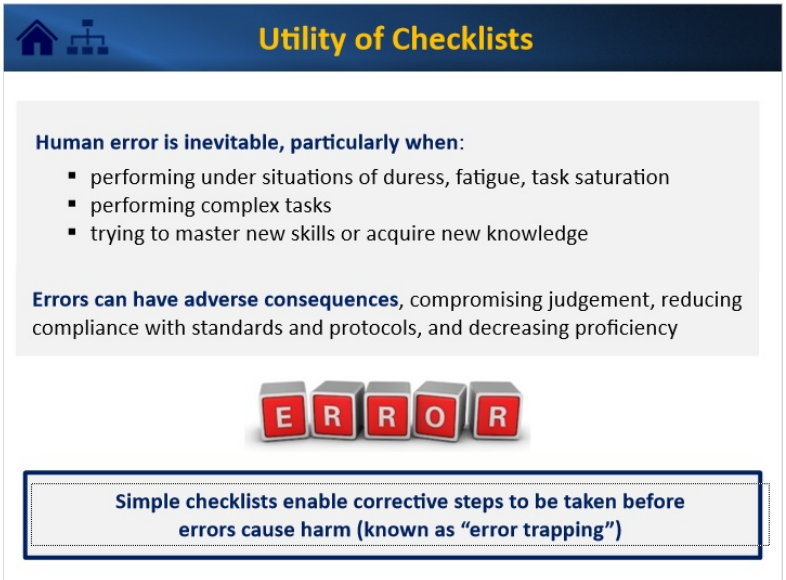


5.3 Topic Selection

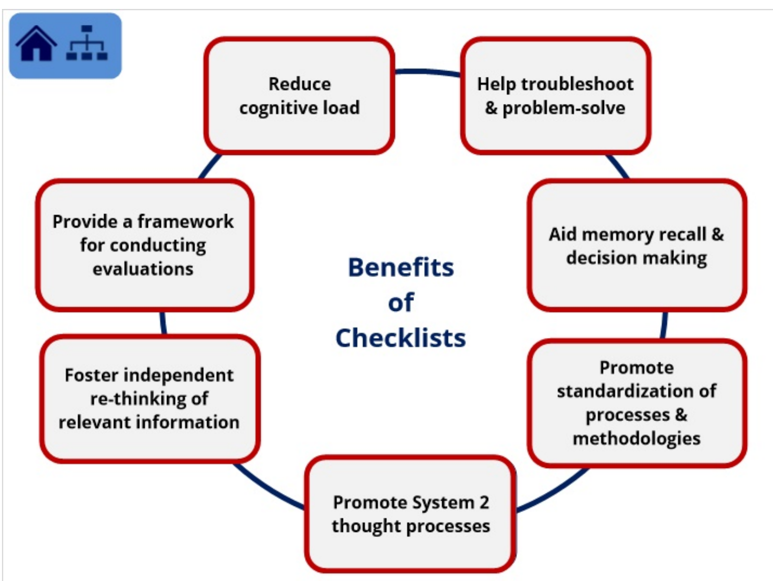


5.4 Bookmark: Checklist Motivations

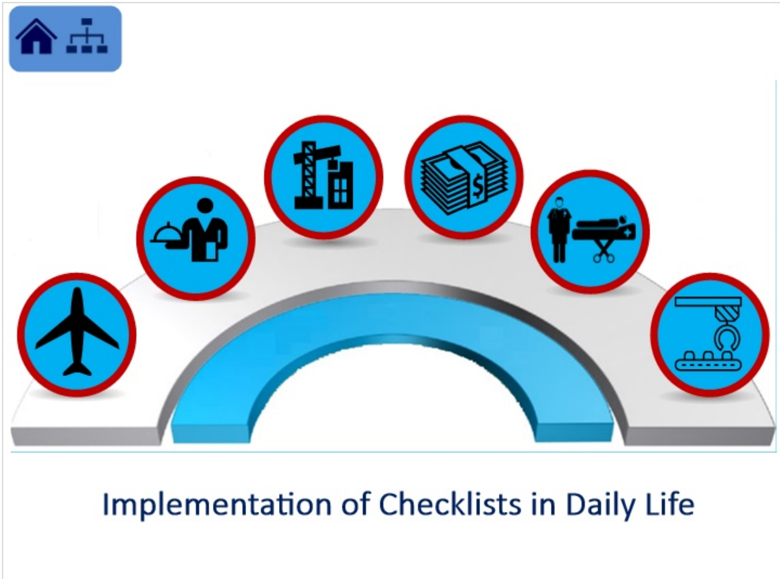
5.5 Utility of Checklists



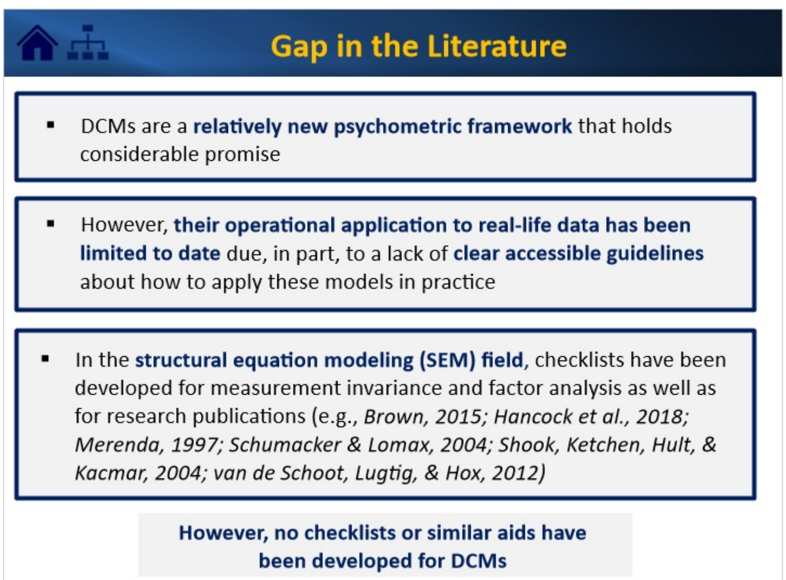
5.6 Benefits of Checklists



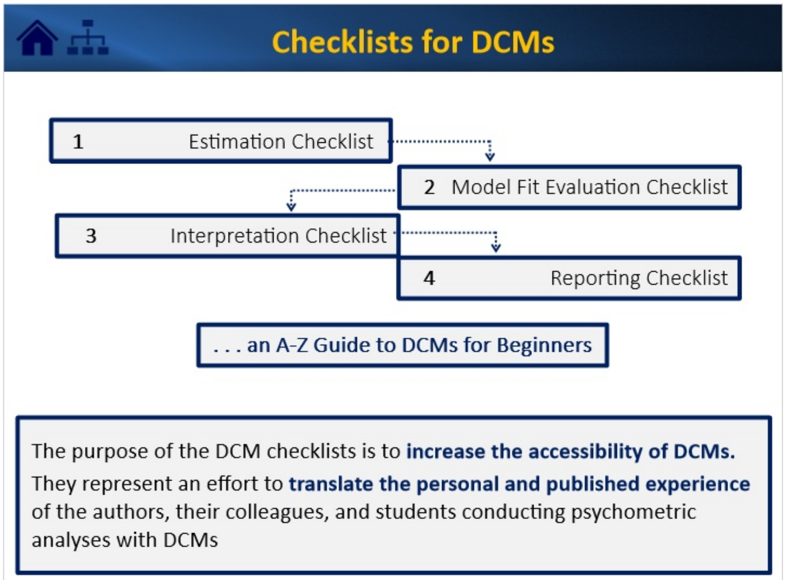
5.7 Checklists in Daily Life



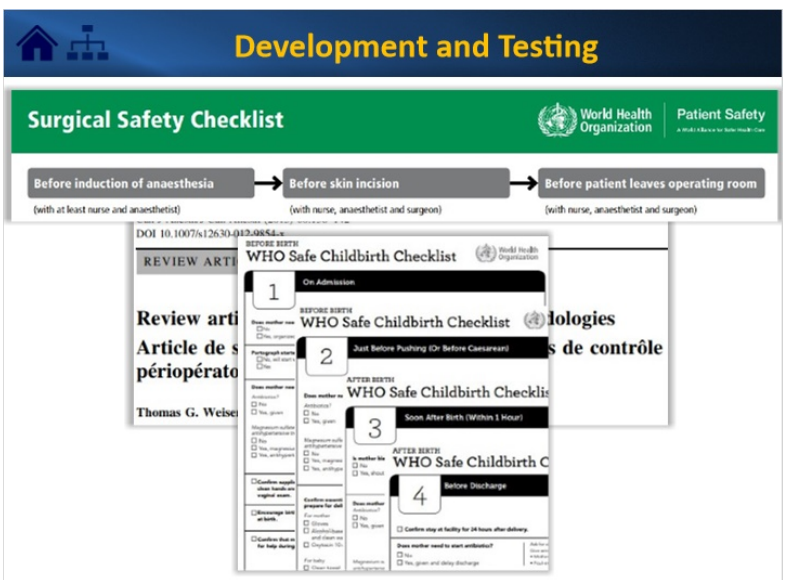
5.8 Gap in the literature



5.9 Checklists for DCMs

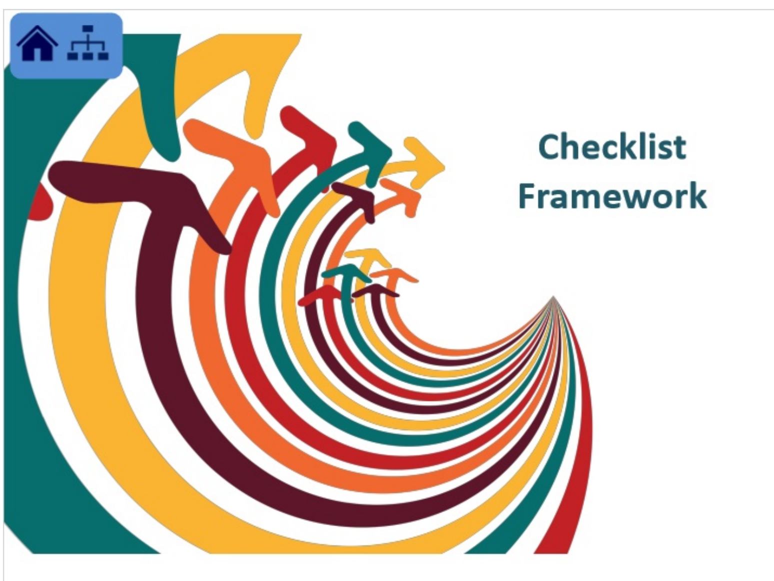


5.10 Development

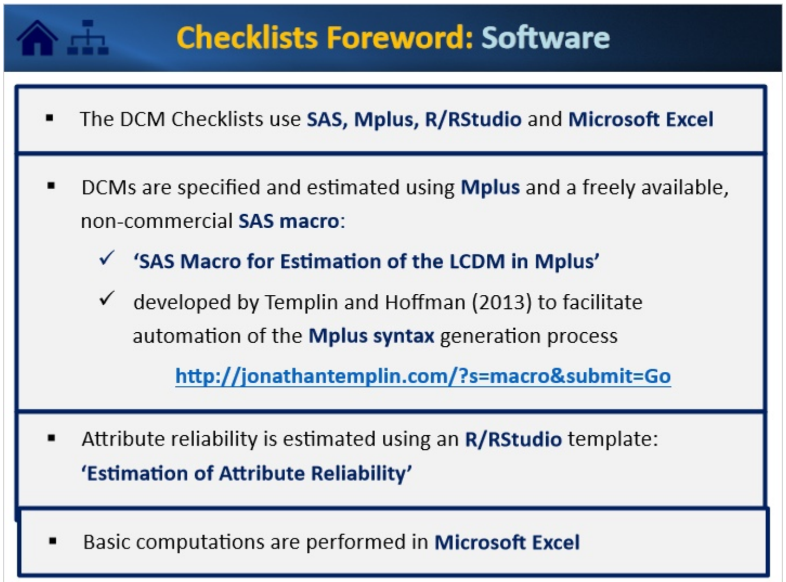


5.11 Bookend: Checklist Motivations

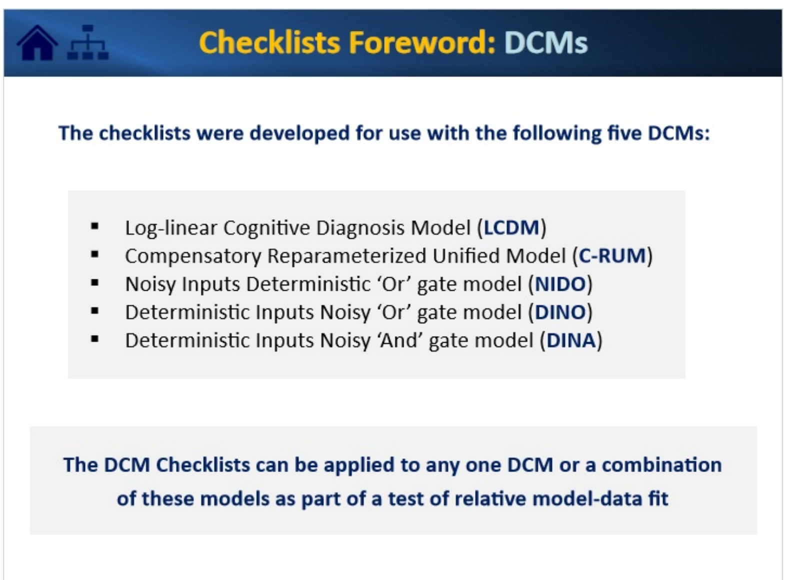
5.12 Bookmark: Checklist Framework



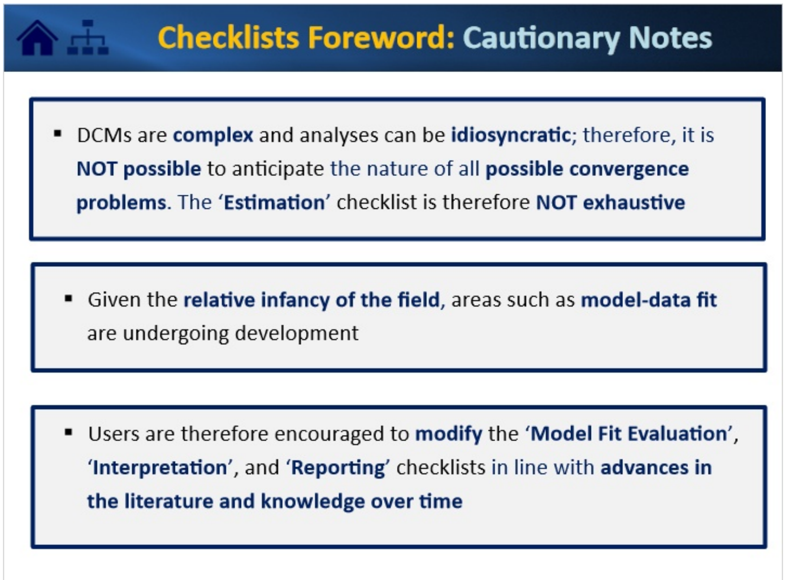
5.13 Checklists Foreword (I)



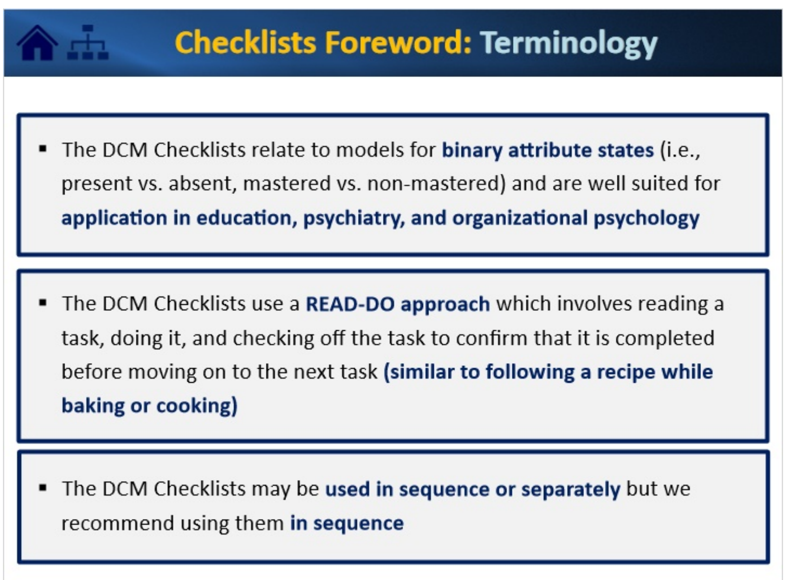
5.14 Checklists Foreword (II)



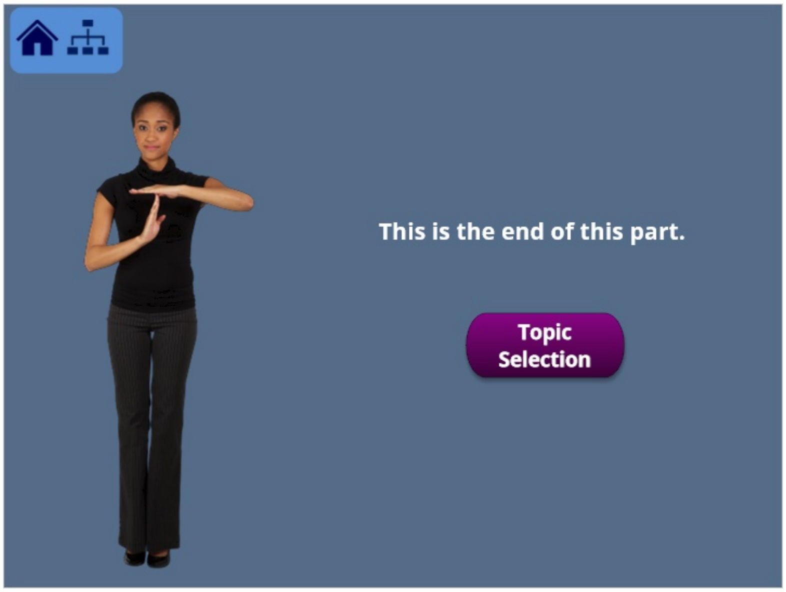
5.15 Checklists Foreword (III)



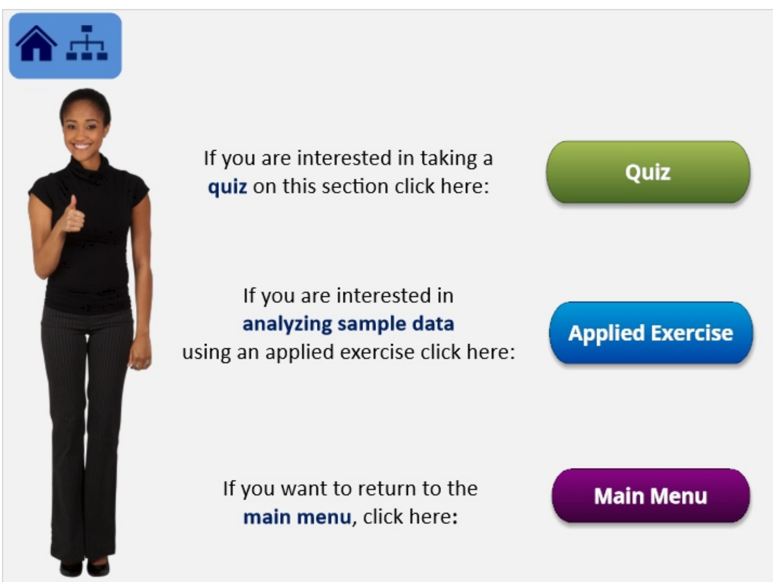
5.16 Checklists Foreword (IV)



5.17 Bookend: Checklist Framework

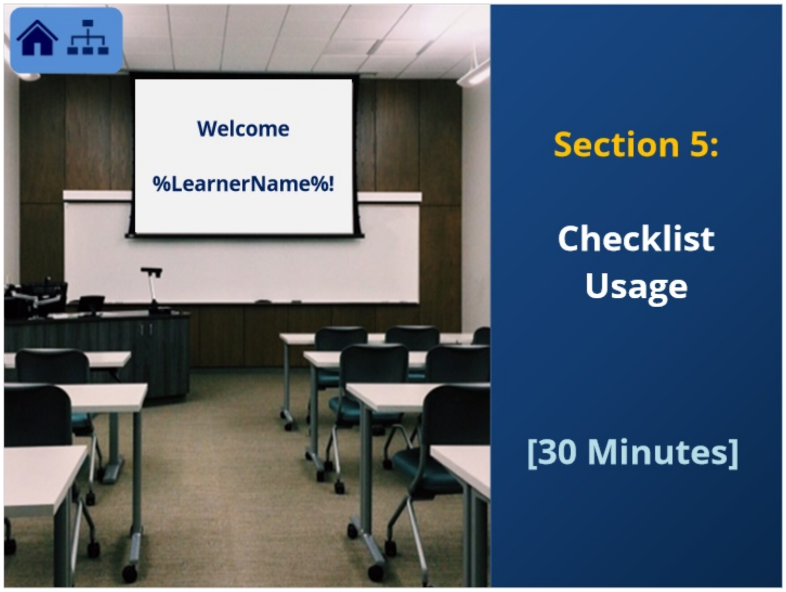


5.18 Bookend: Section 4

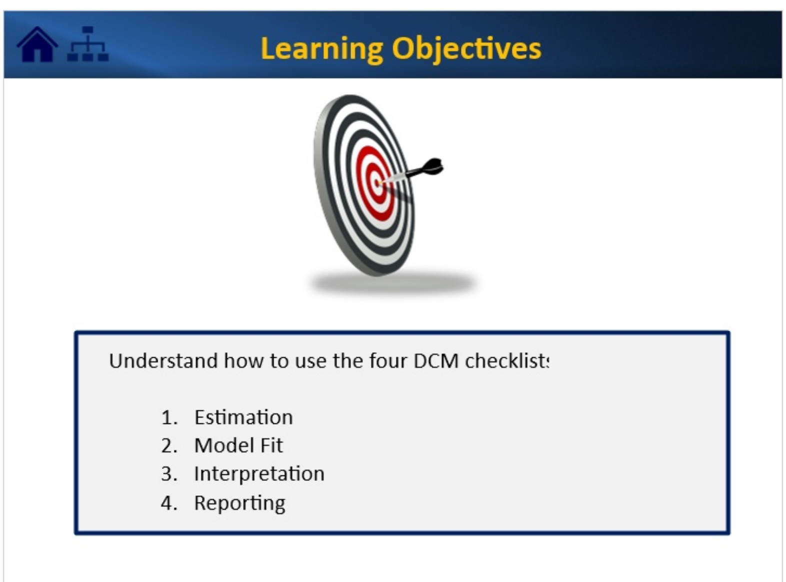


6. Section 5: Checklist Usage

6.1 Cover: Section 5



6.2 Learning Objectives: Section 5



6.3 Data Set

Data Set

- Walk through the '**Model Fit Evaluation**' and '**Interpretation**' checklists to **demonstrate concepts using real-life data** to aid understanding

- Data are derived from a **higher education medical assessment** with **13 psychiatry-related items** assessing **2 broadly defined attributes**:

Attribute 1 (A1) =	Ability to apply clinical knowledge in the assessment of clinical problems
Attribute 2 (A2) =	Ability to apply clinical knowledge in the management of clinical problems

6.4 Companion Files

Companion Files

- **All companion files** related to the data are provided in the '**Resources**' tab of this module and on Jon Templin's website **(click on URL for direct access)**:

https://jonathantemplin.com/ncme-items-module-2019-supplementary-material/

- **Lists of all companion files** are can be accessed via the buttons below.

Input / Output **Model Estimation** **Model Evaluation**

Input / Output (Slide Layer)

Companion Files: Input / Output	
Raw data file: Psychiatry	ITEMSpsychiatry.dat
Q-matrix: Psychiatry	Q matrix ITEMS psychiatry.xlsx
LCDM SAS input file: Psychiatry	ITEMSpsychiatry.sas
LCDM SAS output file (1): Psychiatry LCDM SAS output file (2): Psychiatry LCDM SAS output file (3): Psychiatry LCDM SAS output file (4): Psychiatry LCDM SAS output file (5): Psychiatry LCDM SAS output file (6): Psychiatry LCDM SAS output file (7): Psychiatry LCDM SAS output file (8): Psychiatry LCDM SAS output file (9): Psychiatry LCDM Mplus respondents file: Psychiatry LCDM Mplus input file: Psychiatry LCDM Mplus output file: Psychiatry	psychiatry_attprobrel.sas7bdat psychiatry_classcounts.sas7bdat psychiatry_classmeans.sas7bdat psychiatry_itemparms.sas7bdat psychiatry_qmatrix.sas7bdat psychiatry_readmplus.sas7bdat psychiatry_respondents.sas7bdat psychiatry_ strucparms.sas7bdat psychiatry_thresholds.sas7bdat respondents_ITEMSpsychiatry.dat ITEMSpsychiatry.inp itemspsychiatry.out

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Model Estimation (Slide Layer)

Companion Files: Model Estimation	
Mplus C-RUM file (1): Psychiatry Mplus C-RUM file (2): Psychiatry Mplus C-RUM file (3): Psychiatry Mplus C-RUM file (4): Psychiatry	C-RUM, ITEMSpsychiatry.inp c-rum, itemspsychiatry.out respondents_ITEMSPsychiatry_CRUM.dat ITEMSpsychiatry.dat
Mplus DINA file (1): Psychiatry Mplus DINA file (2): Psychiatry Mplus DINA file (3): Psychiatry Mplus DINA file (4): Psychiatry	DINA, ITEMSpsychiatry.inp dina, itemspsychiatry.out respondents_ITEMSpsychiatry_DINA.dat ITEMSpsychiatry.dat
Mplus DINO file (1): Psychiatry Mplus DINO file (2): Psychiatry Mplus DINO file (3): Psychiatry Mplus DINO file (4): Psychiatry	DINO, ITEMSpsychiatry.inp dino, itemspsychiatry.out respondents_ITEMSPsychiatry_DINO.dat ITEMSpsychiatry.dat
Mplus NIDO file (1): Psychiatry Mplus NIDO file (2): Psychiatry Mplus NIDO file (3): Psychiatry Mplus NIDO file (4): Psychiatry	NIDO, ITEMSpsychiatry.inp nido, itemspsychiatry.out respondents_ITEMSPsychiatry_NIDO.dat ITEMSpsychiatry.dat

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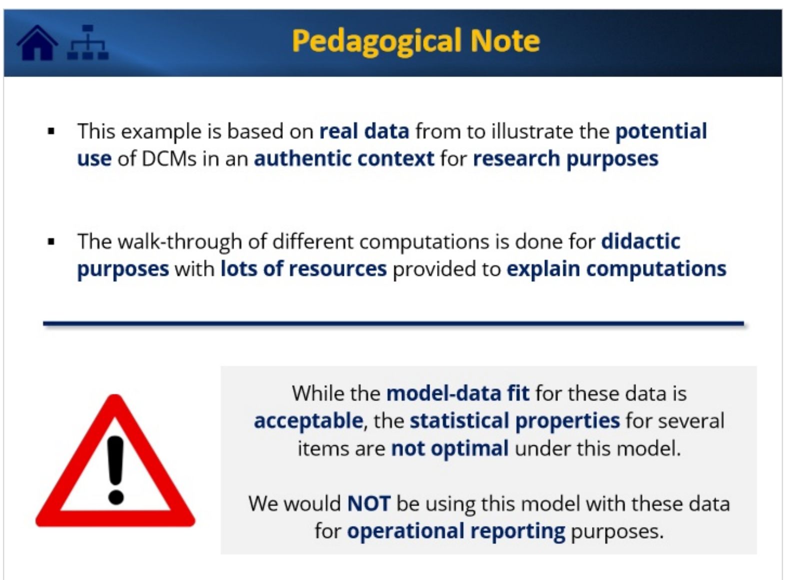
Model Evaluation (Slide Layer)

Companion Files: Model Evaluation	
Attribute reliability file (1): Psychiatry Attribute reliability file (2): Psychiatry Attribute reliability file (3): Psychiatry	Attribute Reliability_Psychiatry.R MplusDCM_functions.R PsychiatryReliability.csv
Loglikelihood ratio calculation: Psychiatry	Loglikelihood ratio calculation psychiatry.xlsx
Attribute mastery profiles: Psychiatry	Attribute mastery profiles psychiatry.xlsx
Diagnostic Score Report: Psychiatry	Diagnostic Score Report psychiatry.pdf
Diagnostic quality of items: Psychiatry	Diagnostic quality of items psychiatry.xlsx
Method and Results write-up: Psychiatry	Method and Results write up psychiatry.pdf
DCM Checklists	DCM Checklists.pdf

Back

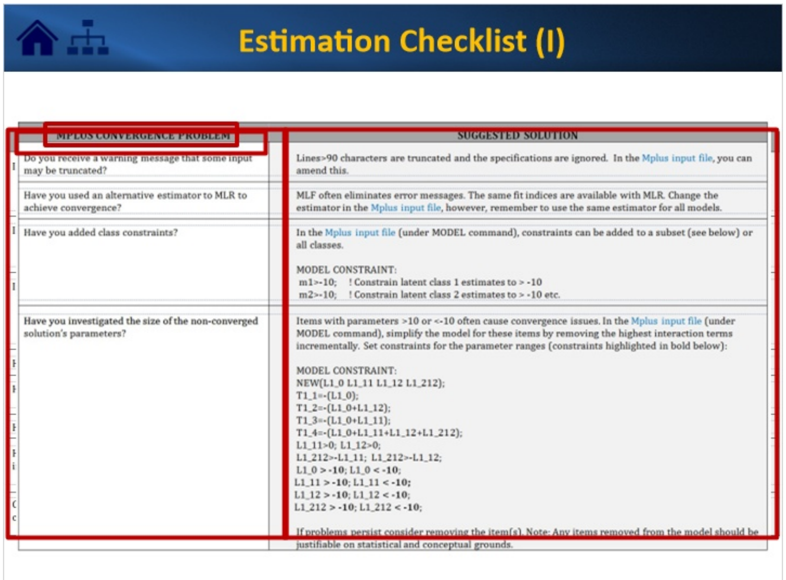
6.5 Pedagogical Note



6.6 Checklist Selection

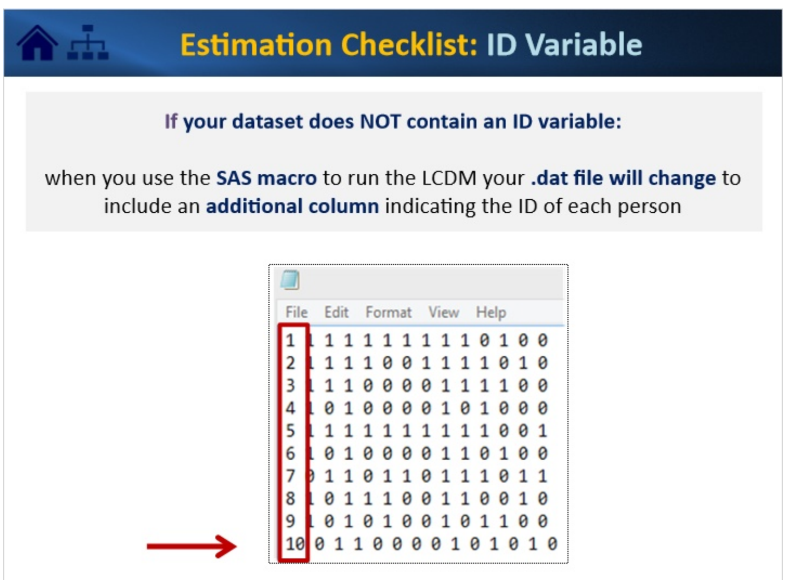
6.7 Bookmark Estimation Checklist

6.8 Estimation Checklist (I)

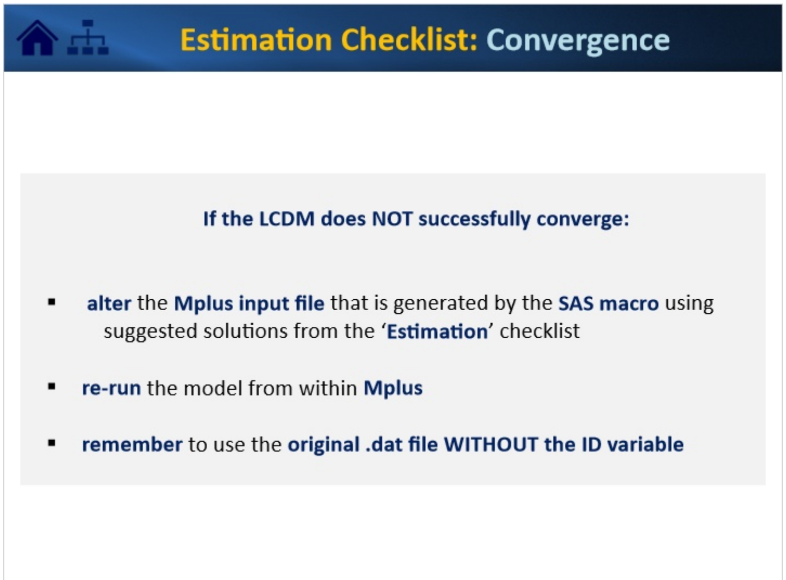


MPLUS CONVERGENCE PROBLEM	SUGGESTED SOLUTION
Do you receive a warning message that some input may be truncated?	Lines>90 characters are truncated and the specifications are ignored. In the Mplus input file, you can amend this.
Have you used an alternative estimator to MLR to achieve convergence?	MLF often eliminates error messages. The same fit indices are available with MLR. Change the estimator in the Mplus input file, however, remember to use the same estimator for all models.
Have you added class constraints?	In the Mplus input file (under MODEL command), constraints can be added to a subset (see below) or all classes. MODEL CONSTRAINT: m1>-10; ! Constrain latent class 1 estimates to > -10 m2>-10; ! Constrain latent class 2 estimates to > -10 etc.
Have you investigated the size of the non-converged solution's parameters?	Items with parameters >10 or <-10 often cause convergence issues. In the Mplus input file (under MODEL command), simplify the model for these items by removing the highest interaction terms incrementally. Set constraints for the parameter ranges (constraints highlighted in bold below): MODEL CONSTRAINT: NEW(L1_0 L1_11 L1_12 L1_212); T1_1=-(L1_0); T1_2=-(L1_0+L1_12); T1_3=-(L1_0+L1_11); T1_4=-(L1_0+L1_11+L1_12+L1_212); L1_11>0; L1_12>0; L1_212>-L1_11; L1_212>-L1_12; L1_0 **> -10**; L1_0 **< -10**; L1_11 **> -10**; L1_11 **< -10;** L1_12 **> -10**; L1_12 **< -10**; L1_212 **> -10**; L1_212 **< -10**; If problems persist consider removing the item(s). Note: Any items removed from the model should be justifiable on statistical and conceptual grounds.

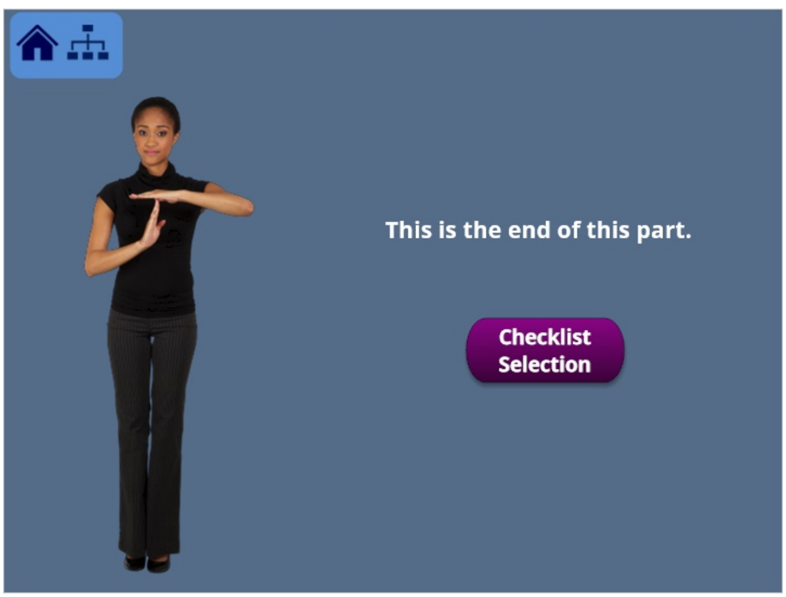
6.9 Estimation Checklist: ID Variable



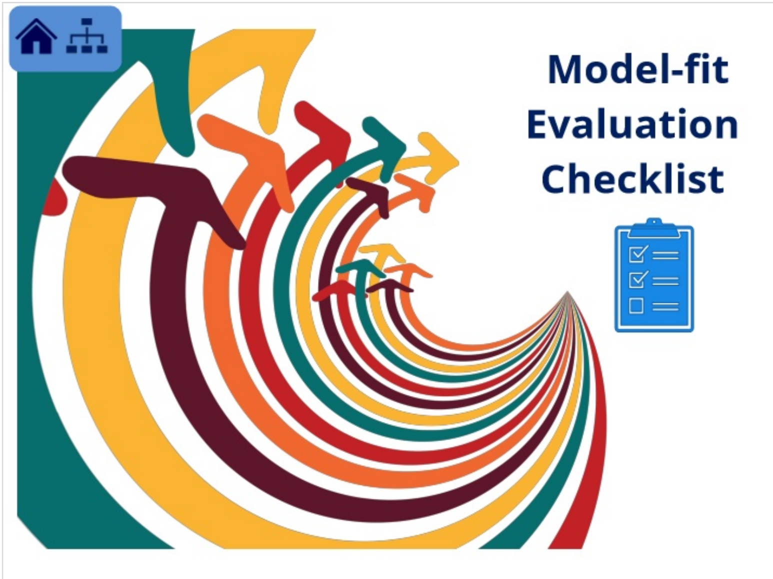
6.10 Estimation Checklist: Convergence



6.11 Bookend: Estimation Checklist



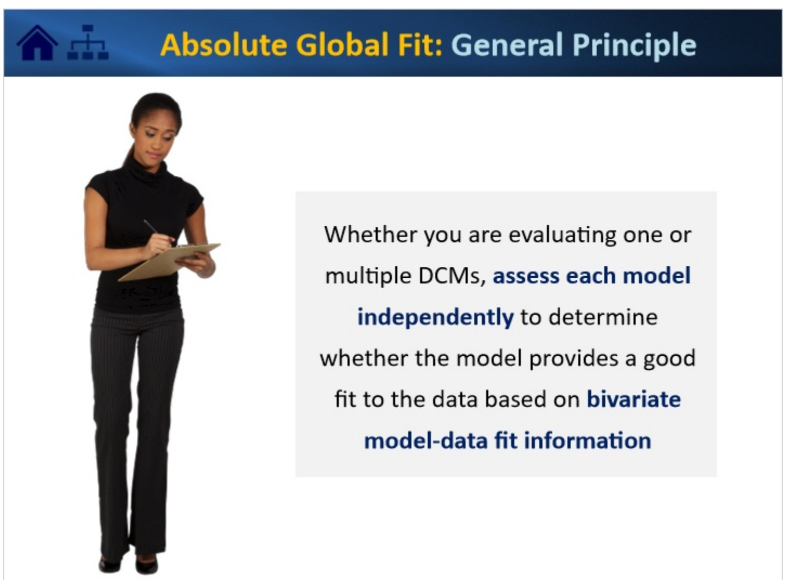
6.12 Bookmark: Evaluation Checklist



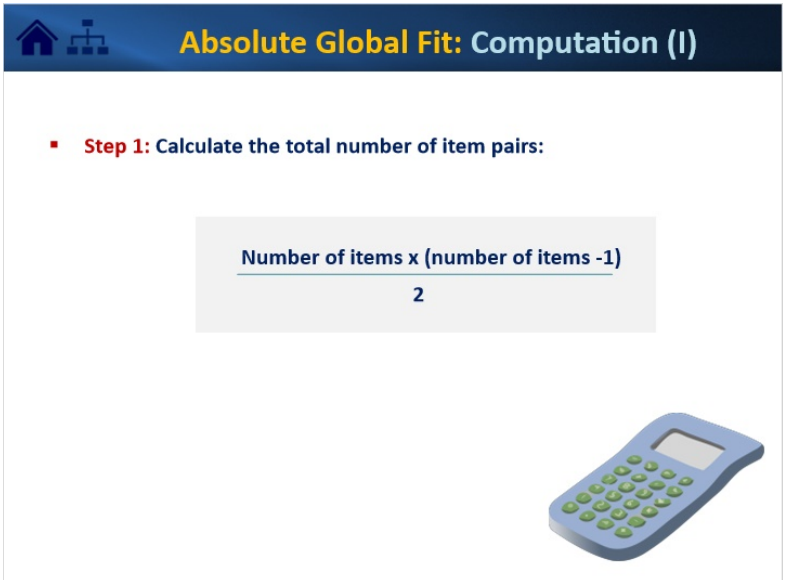
6.13 Model Fit Selection

6.14 Bookmark: Absolute Fit

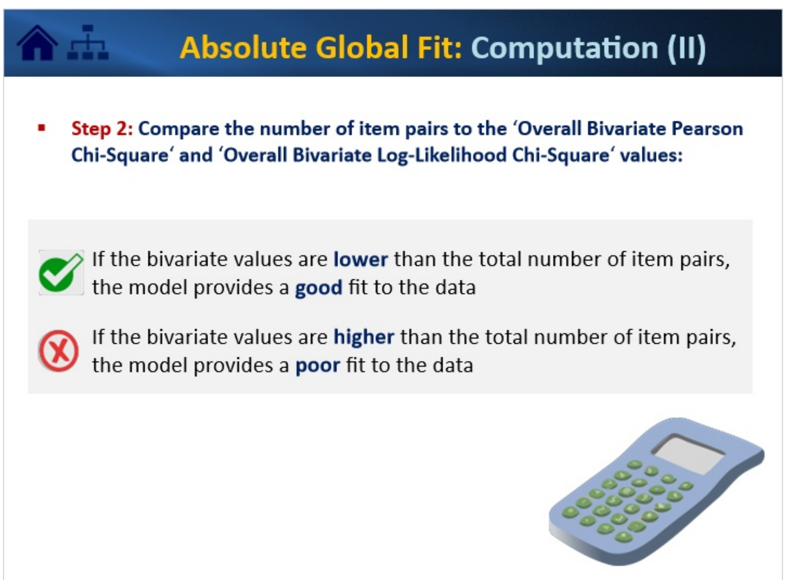
6.15 Absolute Global Fit: General Principle



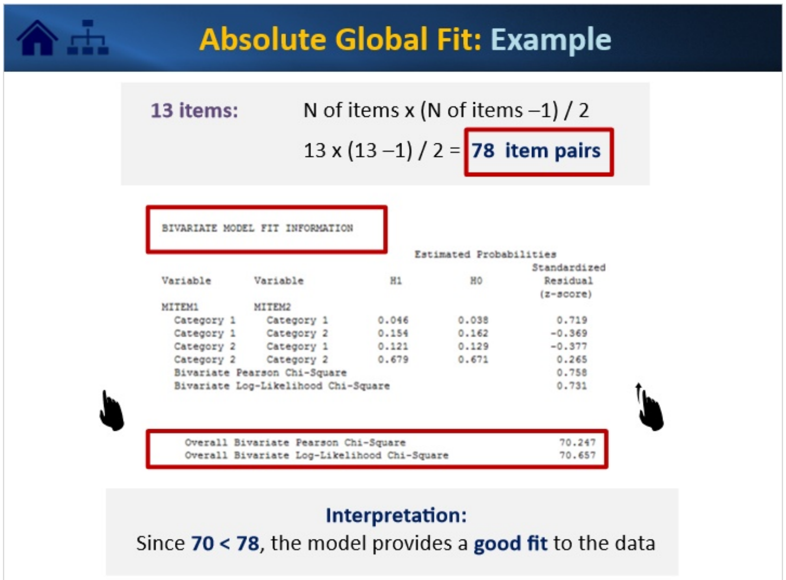
6.16 Absolute Global Fit: Computation (I)



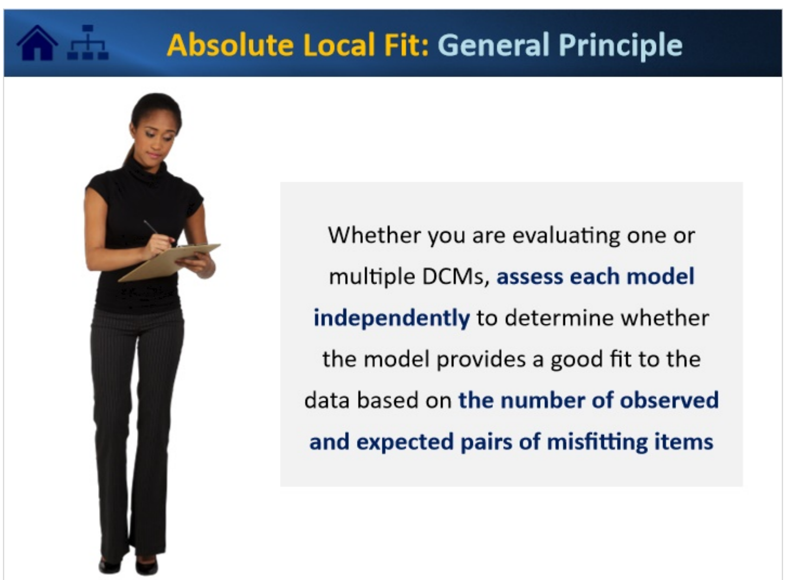
6.17 Absolute Global Fit: Computation (II)



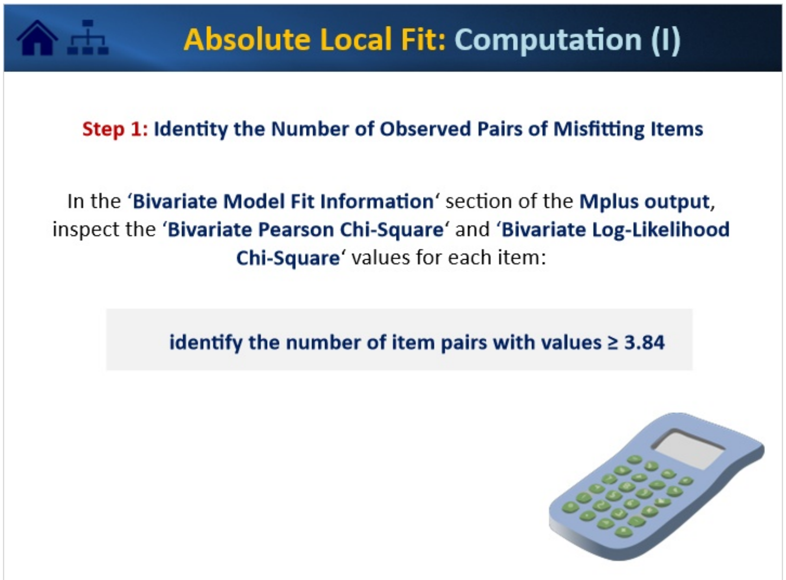
6.18 Absolute Global Fit: Example



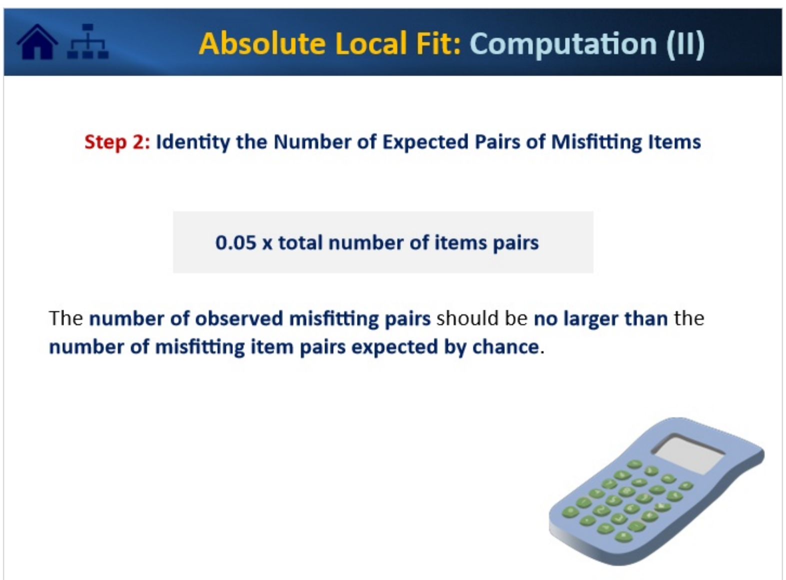
6.19 Absolute Local Fit: General Principle



6.20 Absolute Local Fit: Computation (I)



6.21 Absolute Local Fit: Computation (II)



6.22 Absolute Local Fit: Example (I)

Absolute Local Fit: Example (I)

```
BIVARIATE MODEL FIT INFORMATION

                                        Estimated Probabilities
                                                         Standardized
Variable        Variable              H1           H0      Residual
                                                           (z-score)

MITEM1          MITEM2
  Category 1      Category 1        0.046        0.038         0.719
  Category 1      Category 2        0.154        0.162        -0.369
  Category 2      Category 1        0.121        0.129        -0.377
  Category 2      Category 2        0.679        0.671         0.265
  Bivariate Pearson Chi-Square                                 0.758
  Bivariate Log-Likelihood Chi-Square                          0.731

MITEM4          MITEM9
  Category 1      Category 1        0.050        0.037         1.168
  Category 1      Category 2        0.532        0.545        -0.434
  Category 2      Category 1        0.007        0.020        -1.519
  Category 2      Category 2        0.411        0.398         0.424
  Bivariate Pearson Chi-Square                                 3.768
  Bivariate Log-Likelihood Chi-Square                          4.376
```

Well-fitting item pair (value <3.84)

Misfitting item pair (value > 3.84)

Overall, we observed 4 misfitting item pairs for our data

6.23 Absolute Local Fit: Example (II)

Absolute Local Fit: Example (II)

Calculate the number of misfitting item pairs expected by chance:

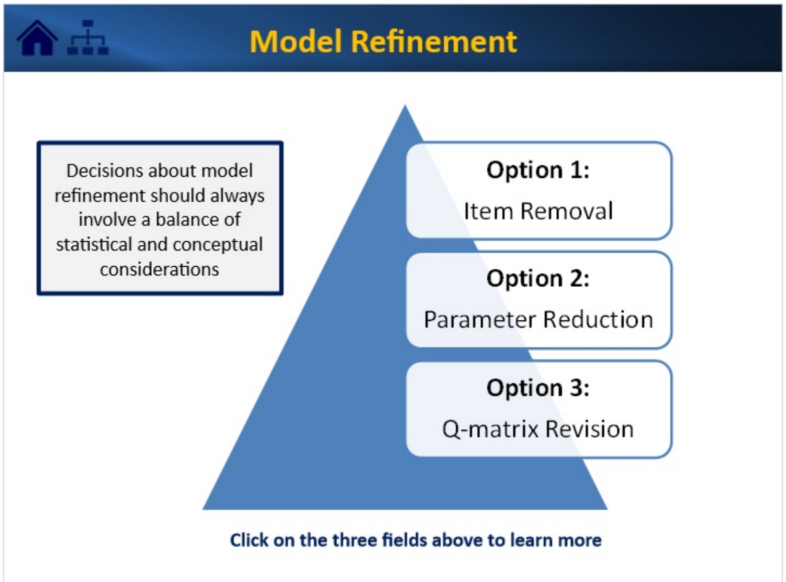
0.05 x total number of item pairs
0.05 x 78 = 4 misfitting item pairs expected by chance

If the number of observed misfitting item pairs is **less than** the number of expected misfitting item pairs, the model provides a **good fit** to the data

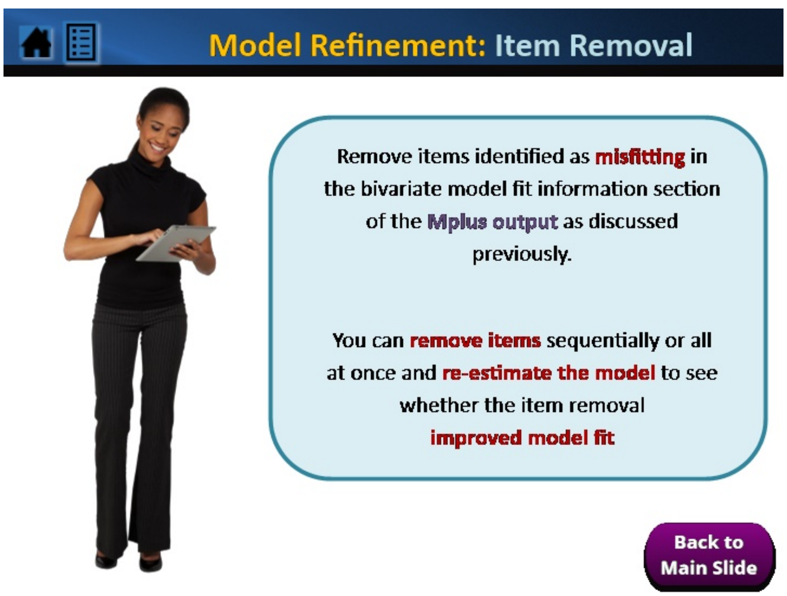
If the number of observed misfitting item pairs is **greater than** the number of expected misfitting item pairs, the model provides a **poor fit** to the data

In this example, there were **4 misfitting item pairs** expected by chance and **4 misfitting item pairs** observed – this means **the model provides a good fit**

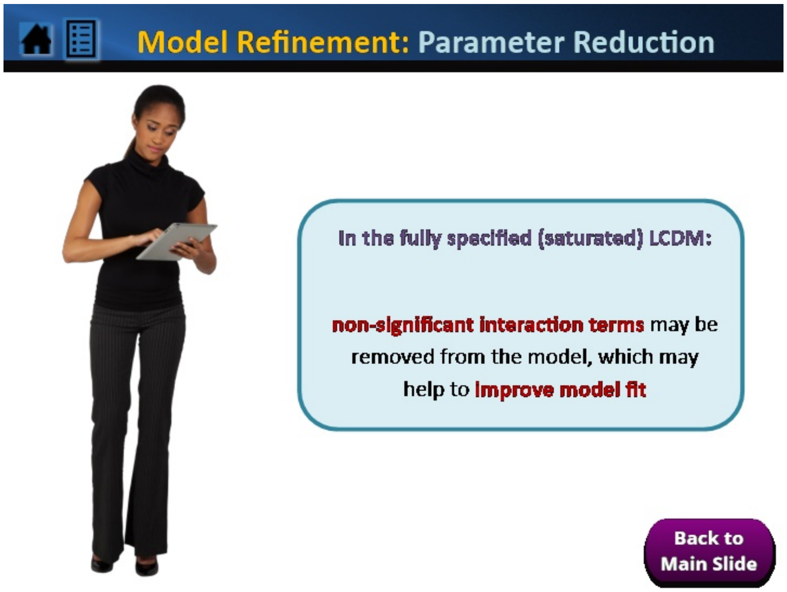
6.24 Model Refinement



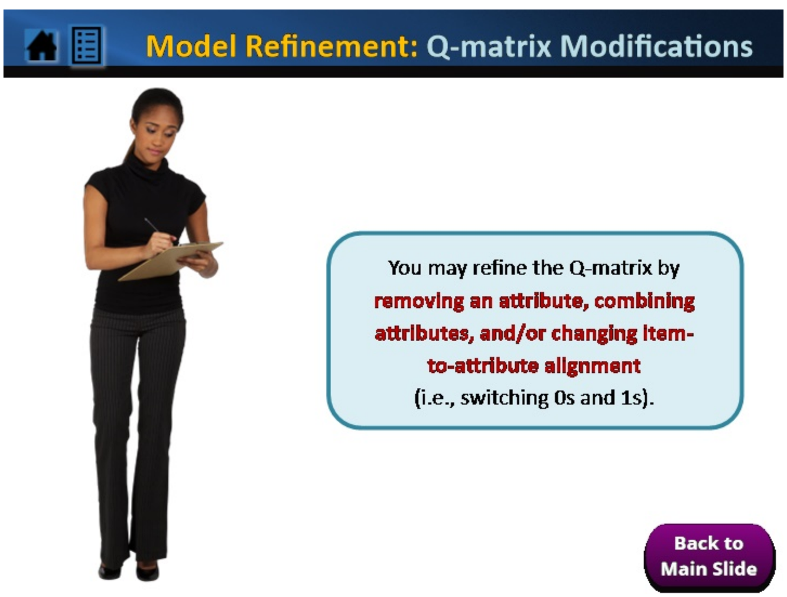
Item Removal (Slide Layer)



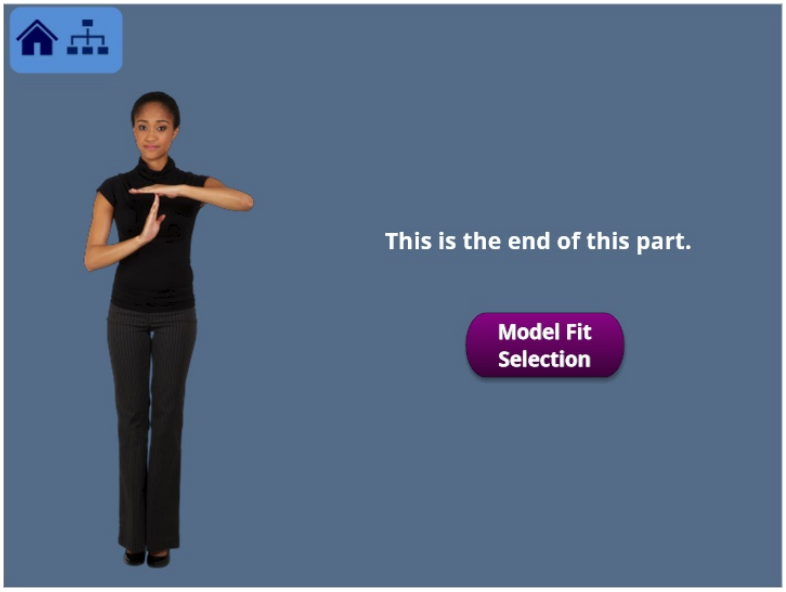
Parameter Reduction (Slide Layer)



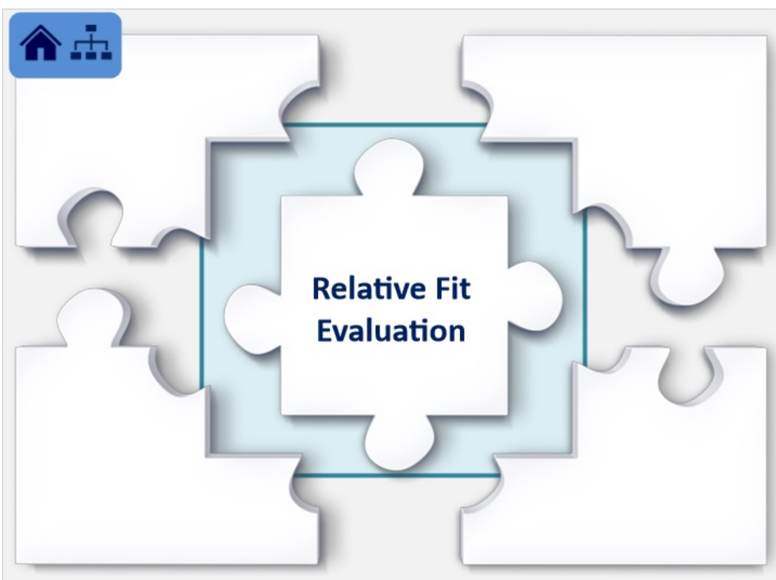
Q-matrix Revision (Slide Layer)



6.25 Bookend: Absolute Fit



6.26 Bookmark: Relative Fit



6.27 Relative Model Fit: General Principles (I)

Relative Model Fit: General Principles (I)

Whenever you are **evaluating multiple DCMs**, only those models displaying **acceptable absolute model** fit should be subsequently **evaluated for relative model fit**

Item Removal (Slide Layer)

Option 1: Removal of misfitting items

- In some cases, the bivariate model fit information may indicate that the model does not provide a good fit to the data. Multiple misfitting items may be observed, with some loading on a single attribute and others loading on multiple attributes.
- Relatedly, if the number of observed misfitting item pairs exceeds the number expected by chance, the user may wish to consider removing problematic items and re-estimating the model to improve model fit.
  - All items *repeatedly* identified as misfitting (i.e., Bivariate Pearson Chi-Square and Bivariate Log-Likelihood Chi-Square' values ≥3.84) could be flagged as candidates for removal in the first instance. These items could be removed sequentially or all at once, and the model re-estimated.

Note: Decisions about model refinement should involve a balance of statistical and conceptual considerations

Only models displaying acceptable absolute model fit should be subsequently evaluated for relative model fit.
Note: Obtaining absolute model fit may be challenging in large samples.

Parameter Reduction (Slide Layer)

Option 2: Removal of non- significant interaction terms (LCDM only)

- As discussed in detail in the DCM Interpretation Checklist (see 'Parameter estimates'), in the LCDM, non-significant interaction terms may be removed from the model. This may help to improve model fit.

Note: Decisions about model refinement should involve a balance of statistical and conceptual considerations

Only models displaying acceptable absolute model fit should be subsequently evaluated for relative model fit.
Note: Obtaining absolute model fit may be challenging in large samples.

Q-matrix Revision (Slide Layer)

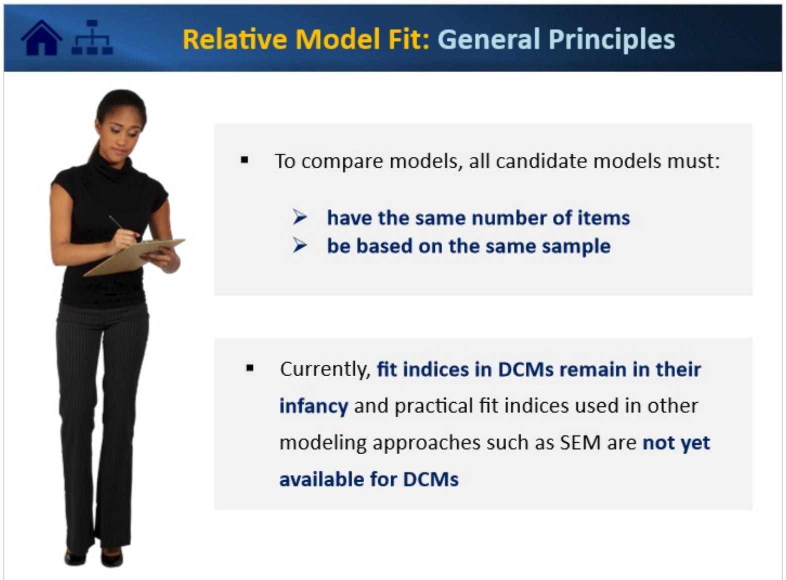
Option 3: Changes to Q-matrix

- The user may wish to consider if there are any empirical misspecifications in the Q-matrix and whether it is necessary to refine the Q-matrix by removing an attribute and/or changing item-to-attribute alignment.

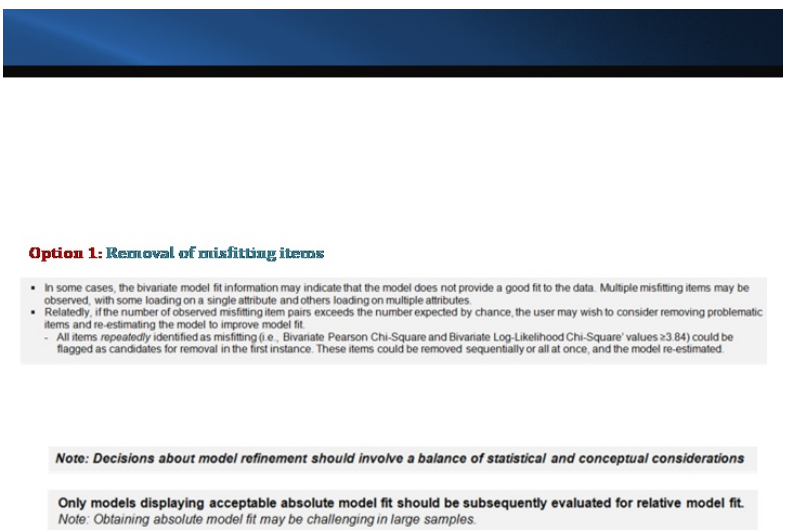
Note: Decisions about model refinement should involve a balance of statistical and conceptual considerations

Only models displaying acceptable absolute model fit should be subsequently evaluated for relative model fit.
Note: Obtaining absolute model fit may be challenging in large samples.

6.28 Relative Model Fit: General Principles



Item Removal (Slide Layer)



Parameter Reduction (Slide Layer)

Option 2: Removal of non- significant interaction terms (LCDM only)

- As discussed in detail in the DCM Interpretation Checklist (see 'Parameter estimates'), in the LCDM, non-significant interaction terms may be removed from the model. This may help to improve model fit.

Note: Decisions about model refinement should involve a balance of statistical and conceptual considerations

Only models displaying acceptable absolute model fit should be subsequently evaluated for relative model fit.
Note: Obtaining absolute model fit may be challenging in large samples.

Q-matrix Revision (Slide Layer)

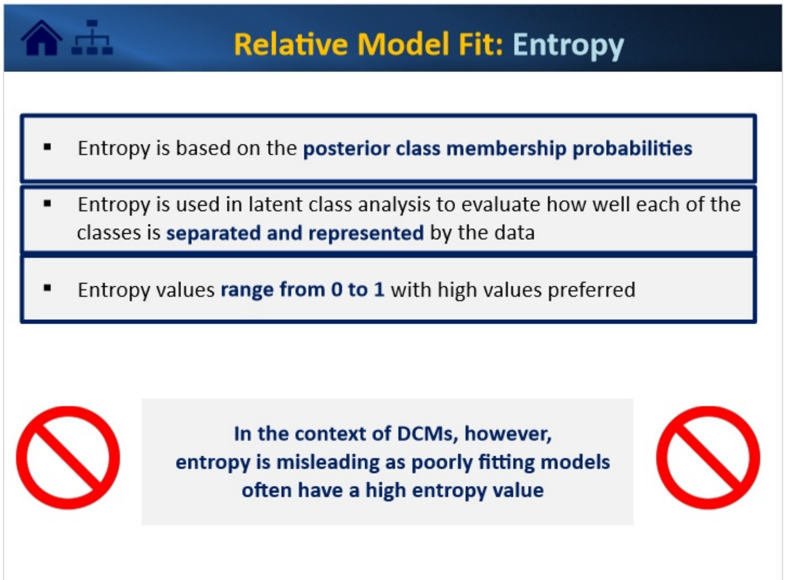
Option 3: Changes to Q-matrix

- The user may wish to consider if there are any empirical misspecifications in the Q-matrix and whether it is necessary to refine the Q-matrix by removing an attribute and/or changing item-to-attribute alignment.

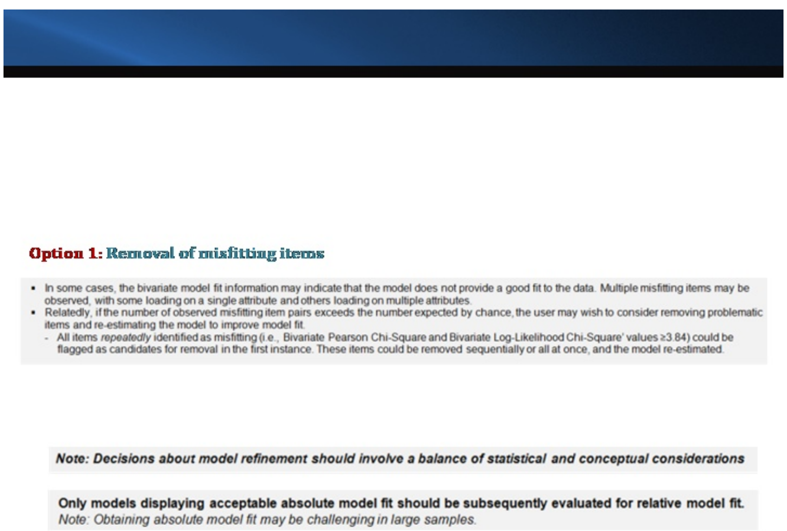
Note: Decisions about model refinement should involve a balance of statistical and conceptual considerations

Only models displaying acceptable absolute model fit should be subsequently evaluated for relative model fit.
Note: Obtaining absolute model fit may be challenging in large samples.

6.29 Relative Model Fit: Entropy

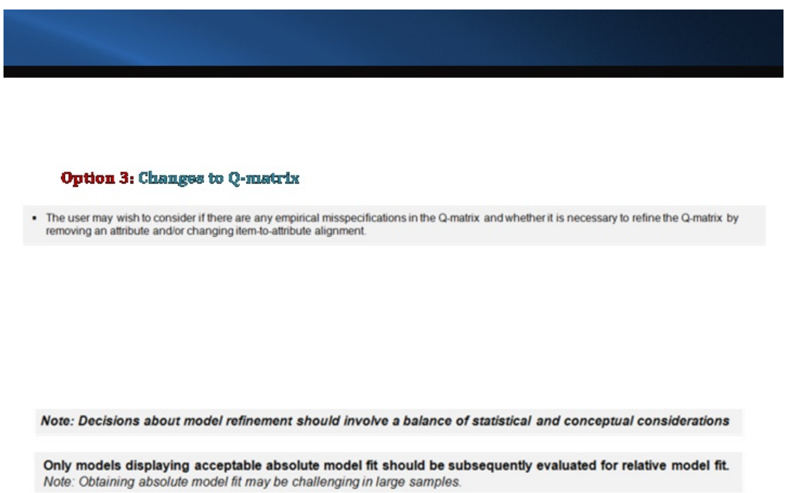


Item Removal (Slide Layer)

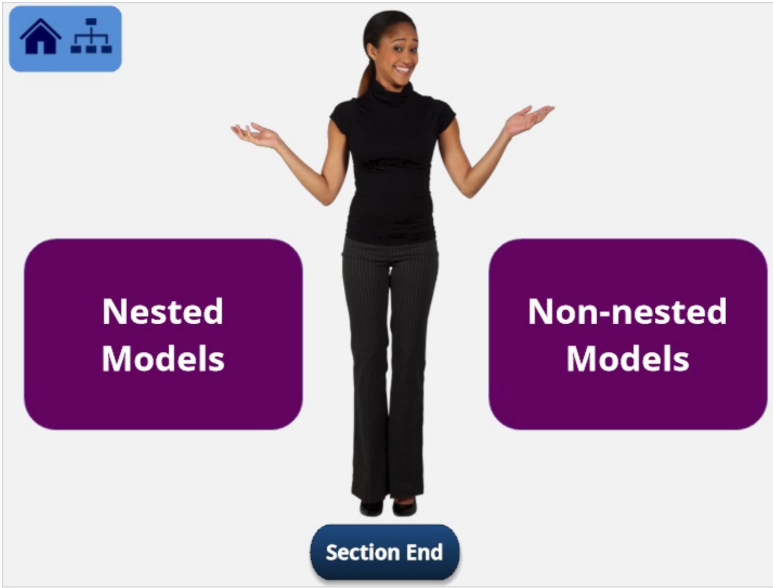


Parameter Reduction (Slide Layer)

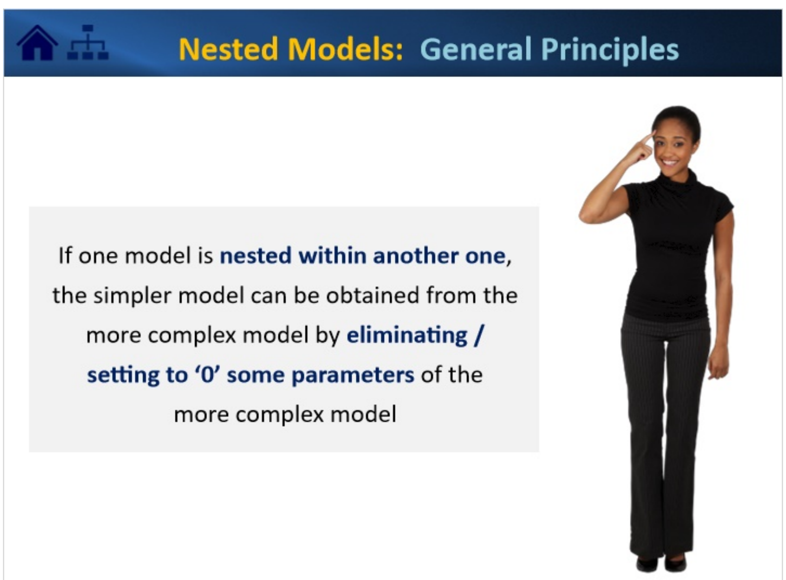
Q-matrix Revision (Slide Layer)



6.30 Model Nesting Selection



6.31 Nested Models: General Principles



6.32 Nested Models: Illustrations

Nested Models: Illustrations

- **A Rasch model** is nested within a two-parameter model
- **A model with one latent dimension (unidimensional model)** is nested within a model with two latent dimensions (multidimensional model)
- **A model with main effect parameters only** is nested within a model that also has interaction effect parameters

6.33 Nested Models: Evaluation

Nested Models: Evaluation

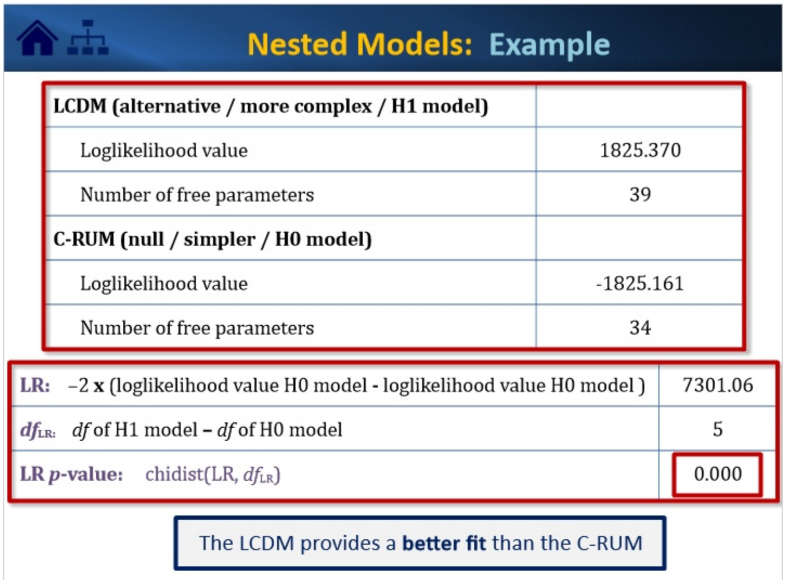
- Locate the '**Model Fit Information**' section in the **Mplus output**

- Retrieve the '**Loglikelihood**' and '**Number of Free Parameters**' values for the null model **(H0: simpler model)** and the alternative model **(H1: more complex model)**

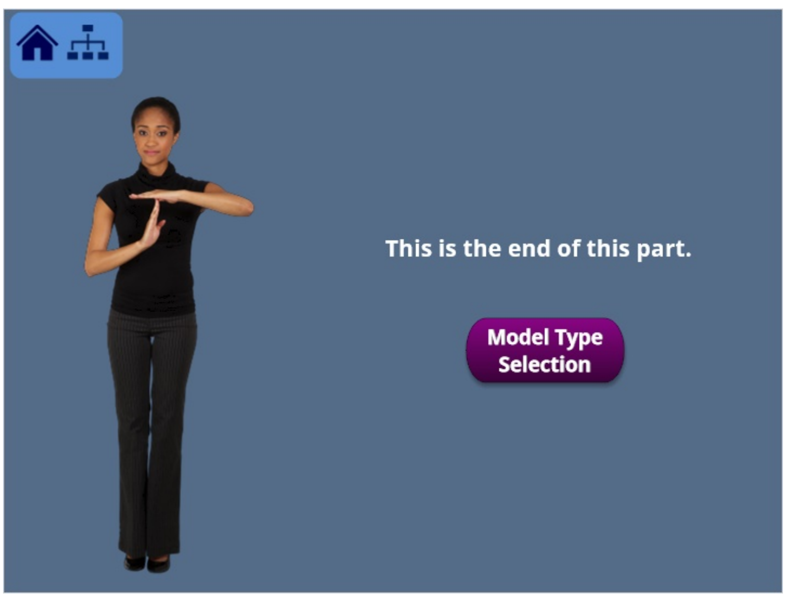
Using Excel, calculate the likelihood ratio test *p*-value:

***p*-value ≥ 0.05** = simpler model provides acceptable fit
***p*-value is < 0.05** = more complex model provides better fit

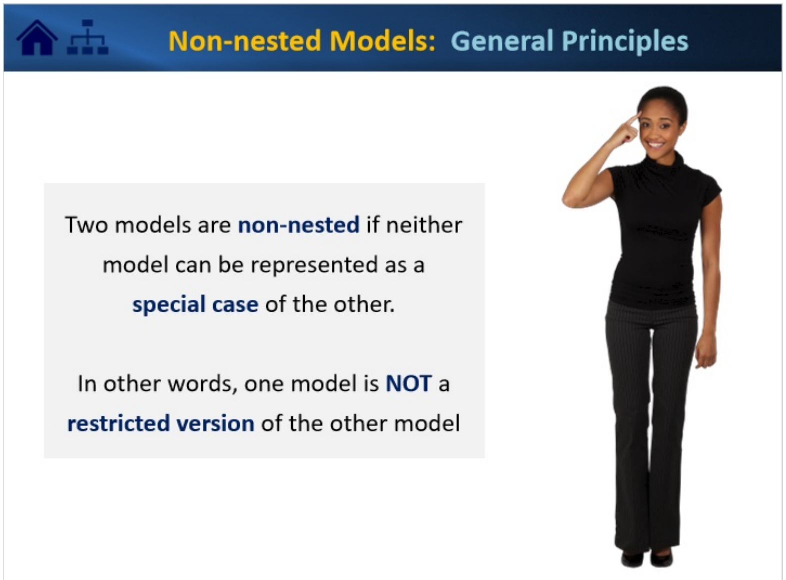
6.34 Nested Models: Example



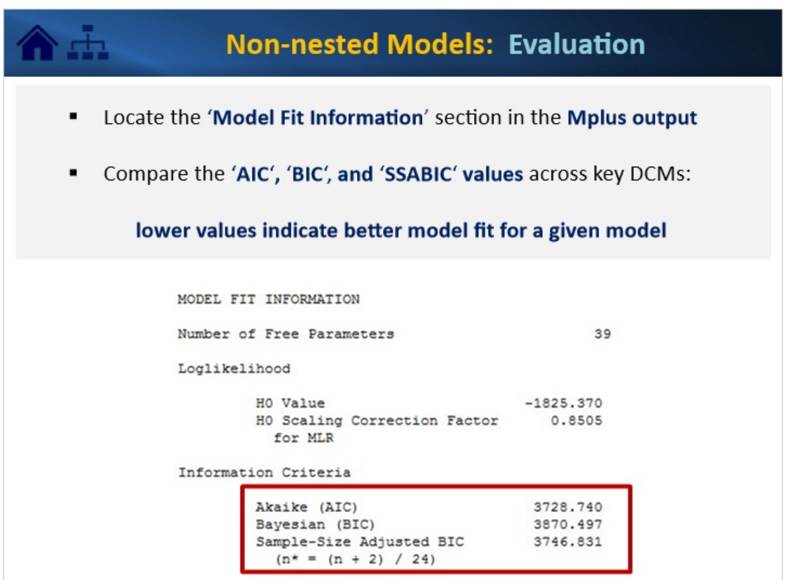
6.35 Bookend: Nested Models



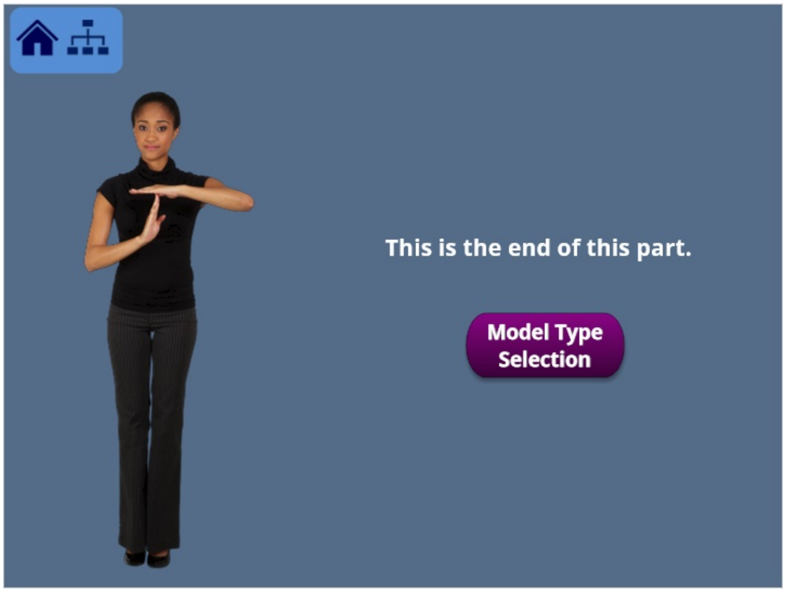
6.36 Non-nested Models: General Principles



6.37 Non-nested Models: Evaluation



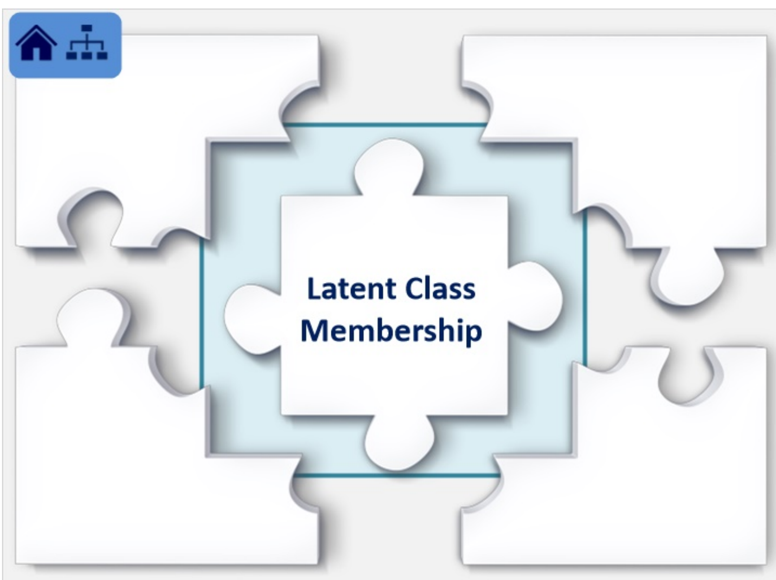
6.38 Bookend: Non-nested Models



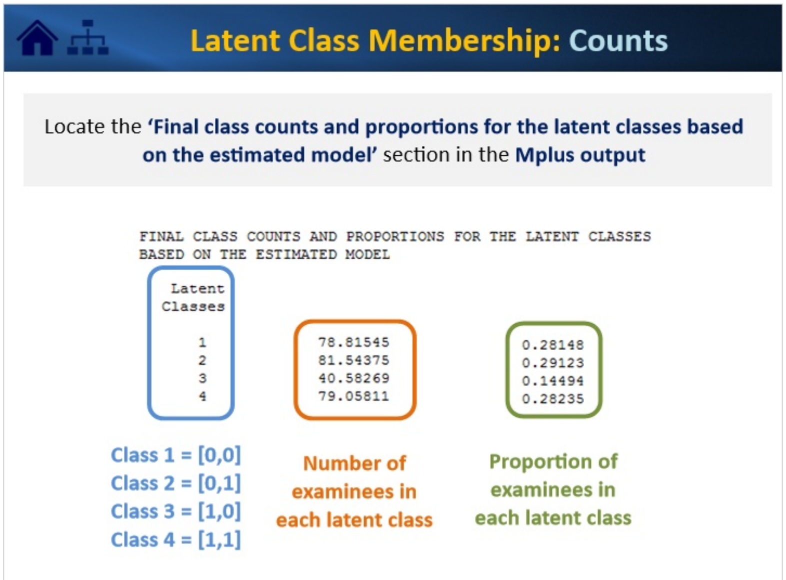
6.39 Bookmark: Interpretation Checklist

6.40 Interpretation Topic Selection

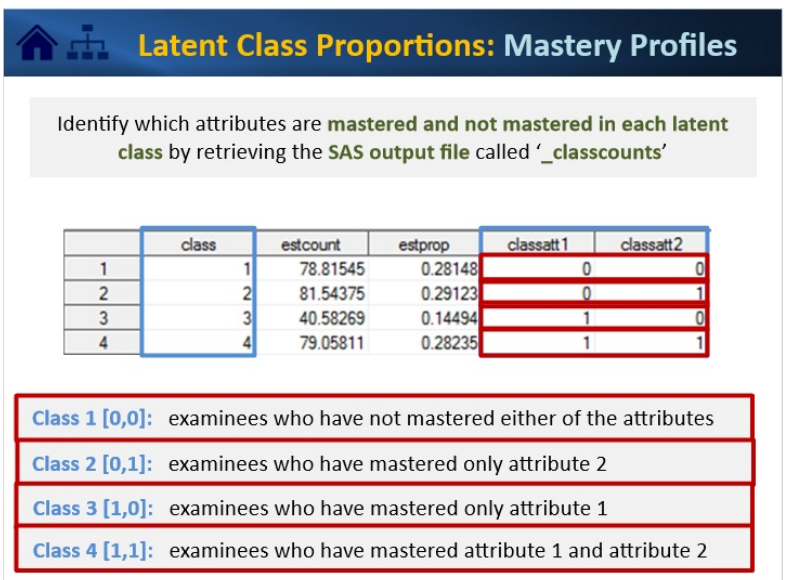
6.41 Bookmark: Membership



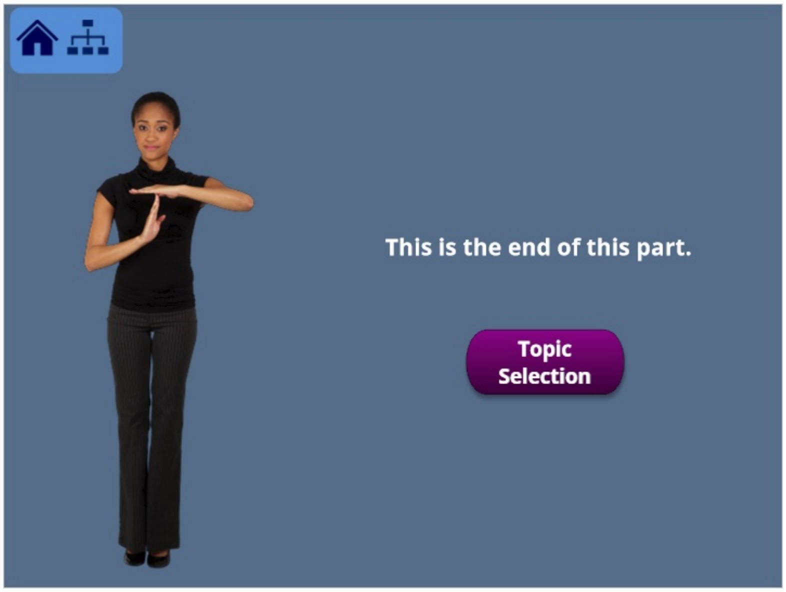
6.42 Latent Class Membership: Counts



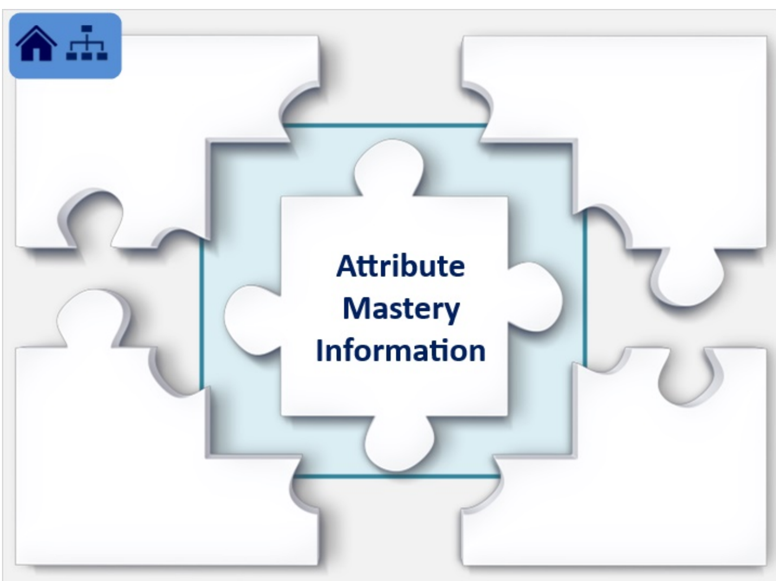
6.43 Latent Class Proportions: Mastery Profiles



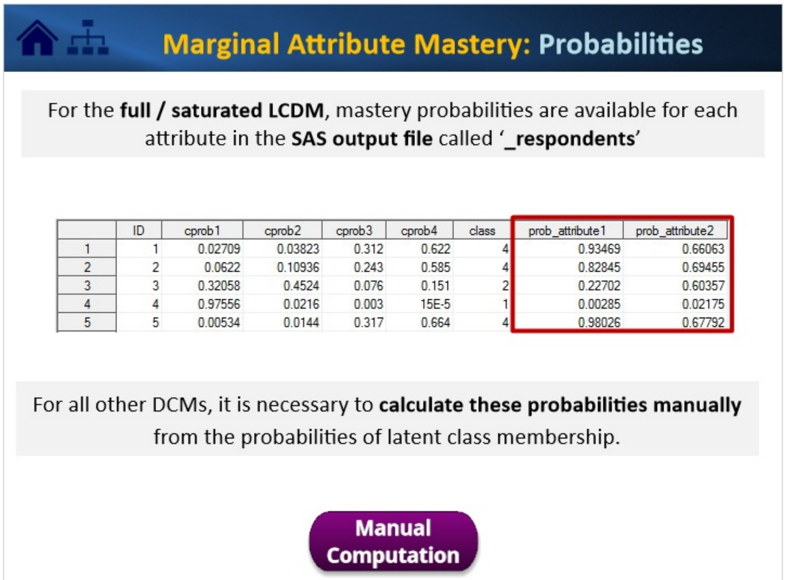
6.44 Bookend: Proportions



6.45 Bookmark: Mastery

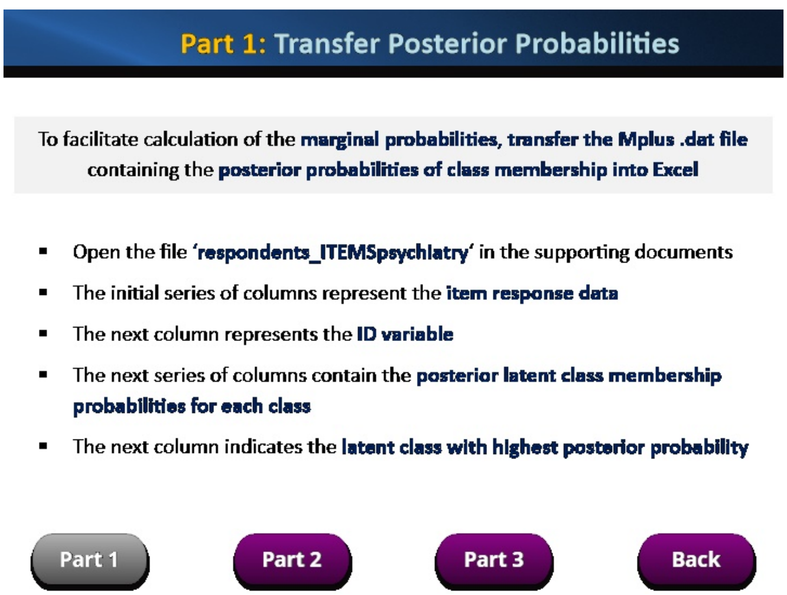


6.46 Marginal Attribute Mastery: Probabilities



	ID	cprob1	cprob2	cprob3	cprob4	class	prob_attribute1	prob_attribute2
1	1	0.02709	0.03823	0.312	0.622	4	0.93469	0.66063
2	2	0.0622	0.10936	0.243	0.585	4	0.82845	0.69455
3	3	0.32058	0.4524	0.076	0.151	2	0.22702	0.60357
4	4	0.97556	0.0216	0.003	15E-5	1	0.00285	0.02175
5	5	0.00534	0.0144	0.317	0.664	4	0.98026	0.67792

Part 1 (Slide Layer)



Part 2 (Slide Layer)

Part 2: Calculate Marginal Probabilities

- For each attribute, use the **SUM function in Excel** to calculate the marginal probability of mastery for each attribute as the **sum of the latent class membership probabilities** across all of the latent classes for which the attribute is actually **mastered**
- Since **latent class membership is mutually exclusive**, the sum of all probabilities across all latent classes is always 1 and computing sums is a legitimate statistical operation for this purpose
- Perform this equation for examinee 1. **Drag the formula down the column to fill the remaining cells.** Repeat for each attribute.

Part 1 | Part 2 | Part 3 | Back

Part 3 (Slide Layer)

Part 3: Example

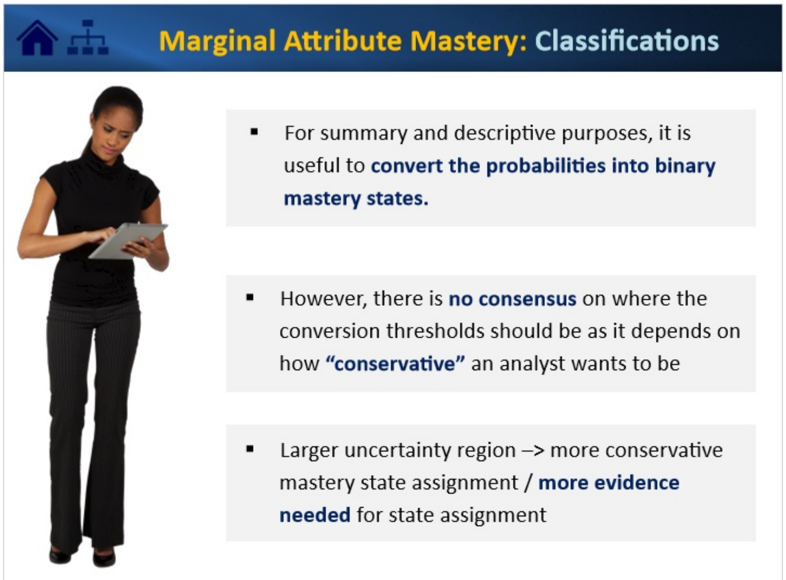
	Q	R	S	T	V	X	Y
15	Posterior latent class membership probability				Latent class with highest posterior probability	Marginal probabilities	
16	Latent class 1 [0,0]	Latent class 2 [0,1]	Latent class 3 [1,0]	Latent class 4 [1,1]		Attribute 1: [0,0,1,1]	Attribute 2: [0,1,0,1]
17	0.02709	0.03823	0.31229	0.6224	4	0.93469	0.66063
18	0.0622	0.10936	0.24326	0.58519	4	0.82845	0.69455
19	0.32058	0.4524	0.07585	0.15117	2	0.22702	0.60357
20	0.97556	0.0216	0.0027	0.00015	1	0.00285	0.02175
21	0.00534	0.0144	0.31674	0.66352	4	0.98026	0.67792
22	0.58578	0.40042	0.00762	0.00618	1	0.0138	0.4066

=SUM(Q17*(0),R17*(0),S17*(1),T17*(1))

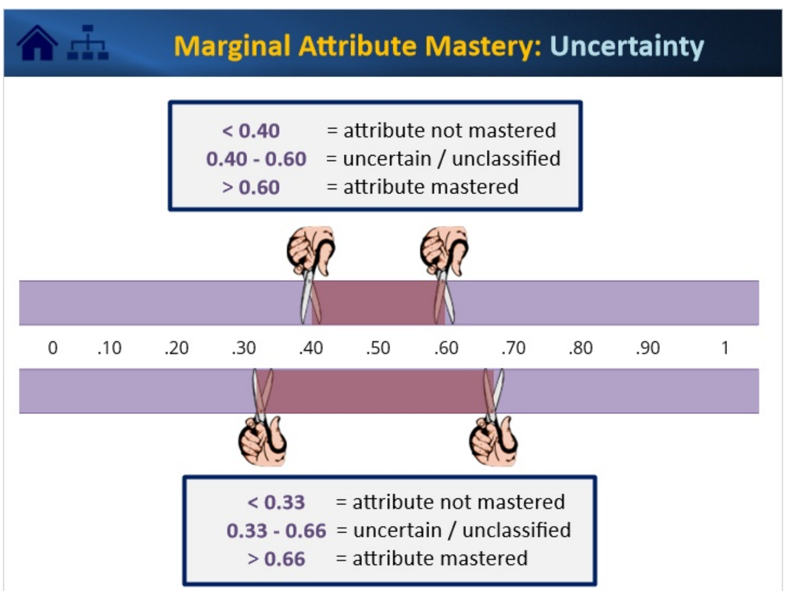
=SUM(Q17*(0),R17*(1),S17*(0),T17*(1))

Part 1 | Part 2 | Part 3 | Back

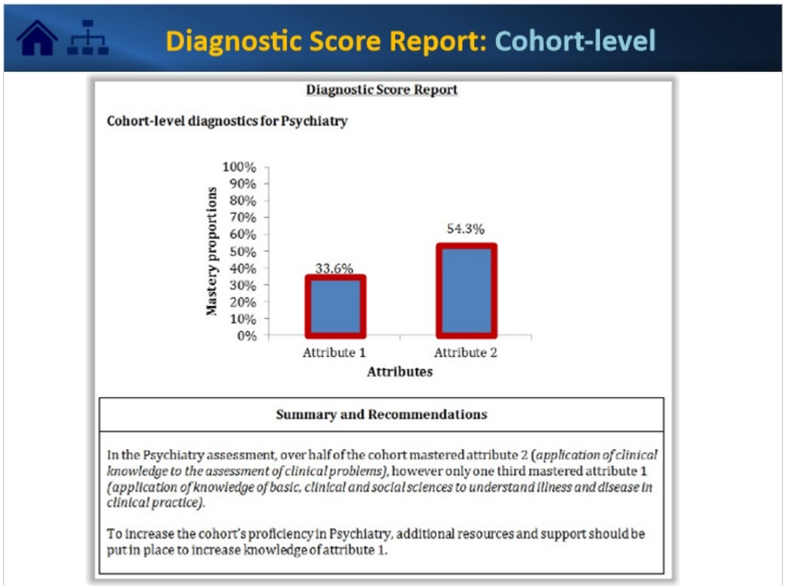
6.47 Marginal Attribute Mastery: Classifications



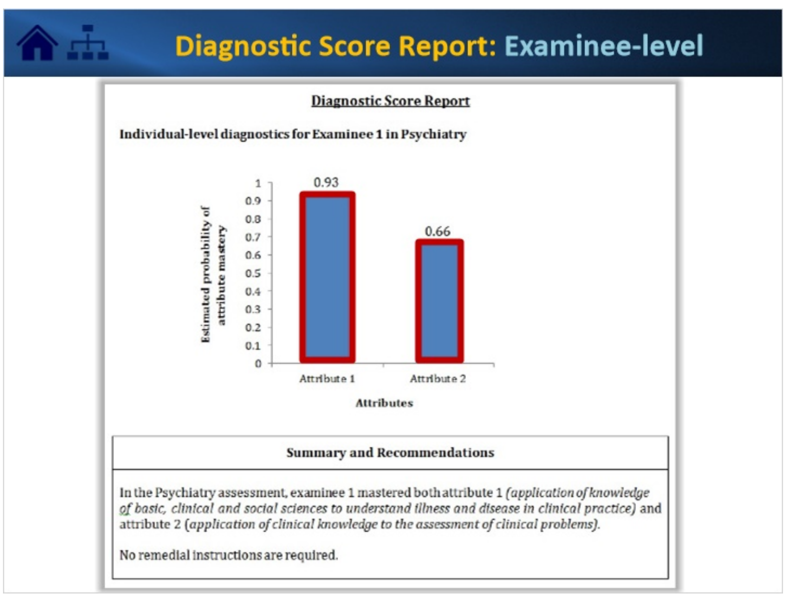
6.48 Marginal Attribute Mastery: Uncertainty



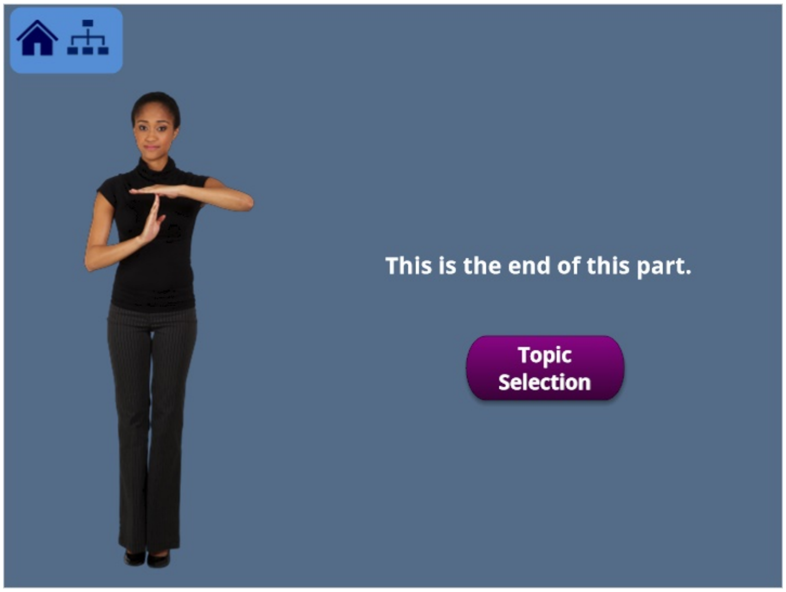
6.49 Diagnostic Score Report: Cohort-level



6.50 Diagnostic Score Report: Examinee-level

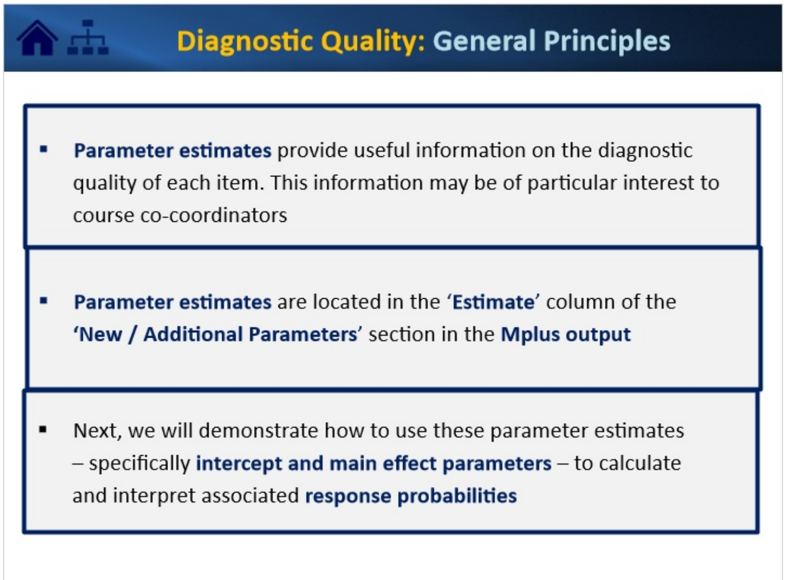


6.51 Bookend: Mastery



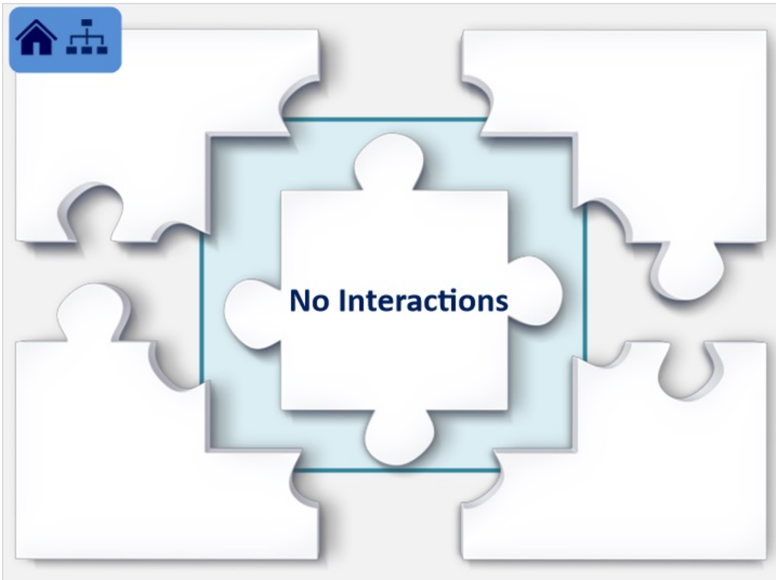
6.52 Bookmark: Quality

6.53 Diagnostic Quality: General Principles

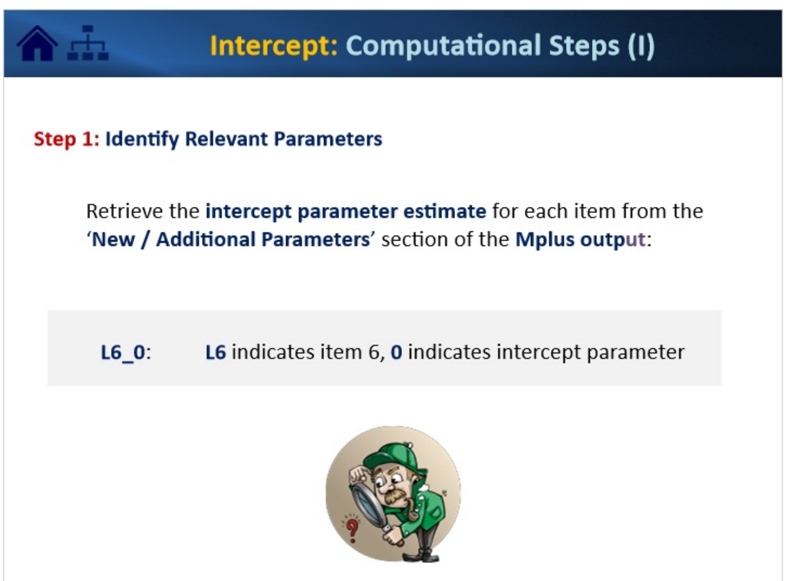


6.54 Interaction Selection

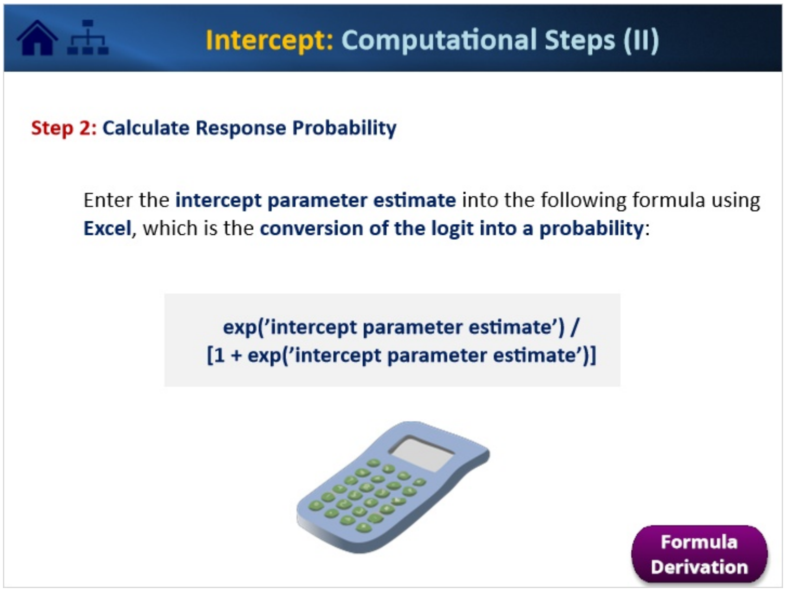
6.55 Bookmark: No Interactions



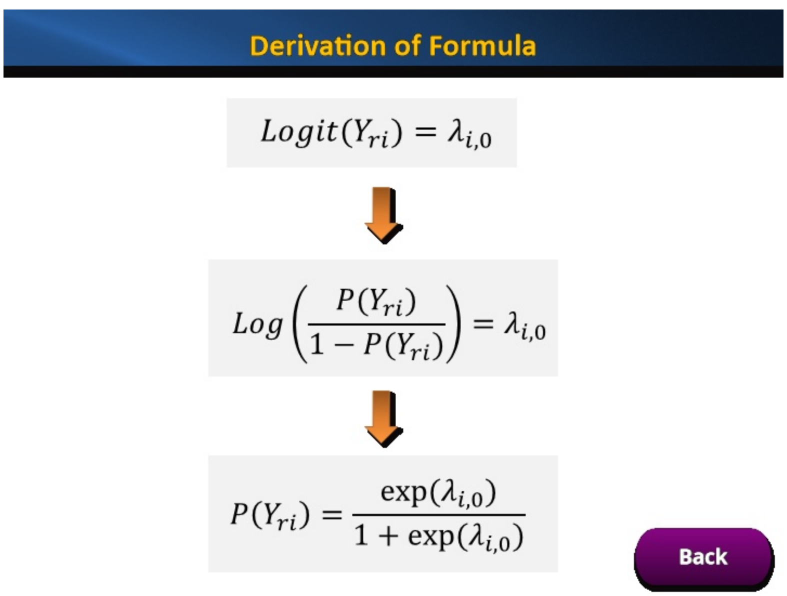
6.56 Intercept: Computational Steps (I)



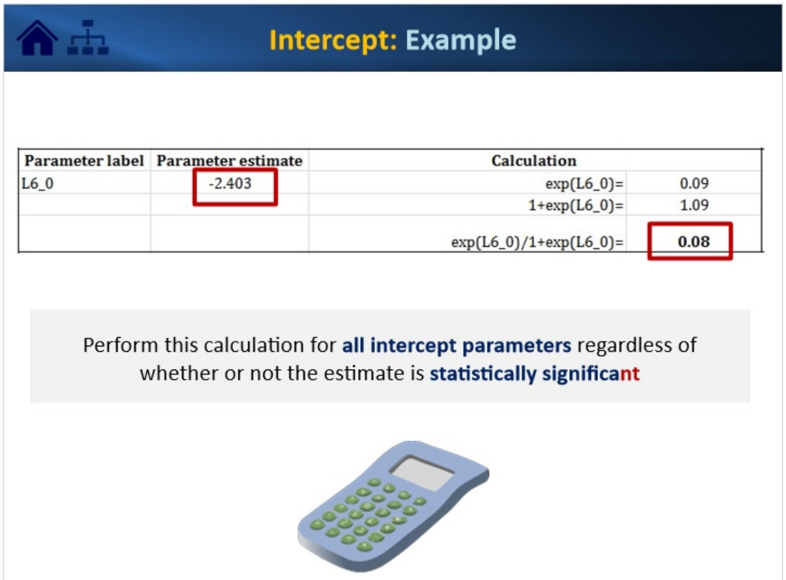
6.57 Intercept: Computational Steps (II)



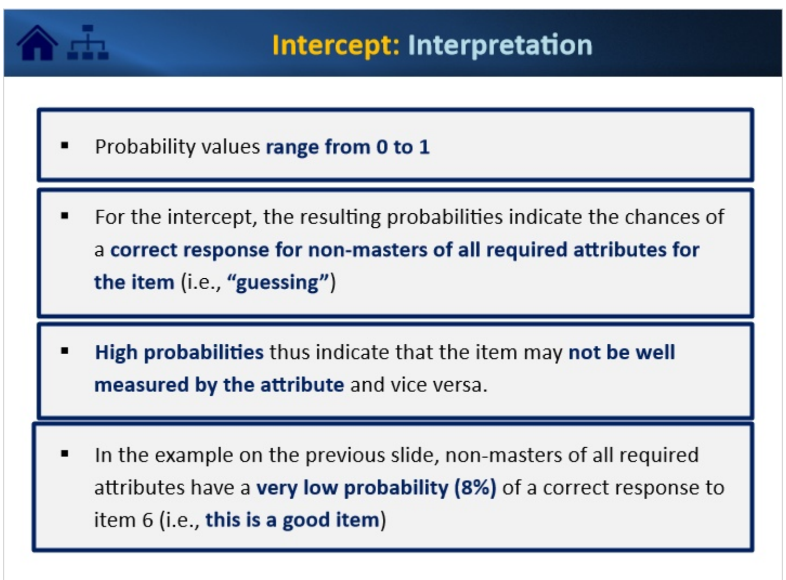
Derivation (Slide Layer)



6.58 Intercept: Example



6.59 Intercept: Interpretation



6.60 Main Effect: Computational Steps (I)

Main Effect: Computational Steps (I)

Step 1: Identify Relevant Parameters

Retrieve the **main effect parameter estimate** for each item from the **'New / Additional Parameters'** section of the **Mplus output**:

L6_11:

- **L6** indicates **item 6**
- the first '**1**' after the underscore indicates a **main effect**
- the second '**1**' after the underscore indicates that this item measures **attribute 1**

6.61 Main Effect: Computational Steps (II)

Main Effect: Computational Steps (II)

Step 2: Calculate Response Probability

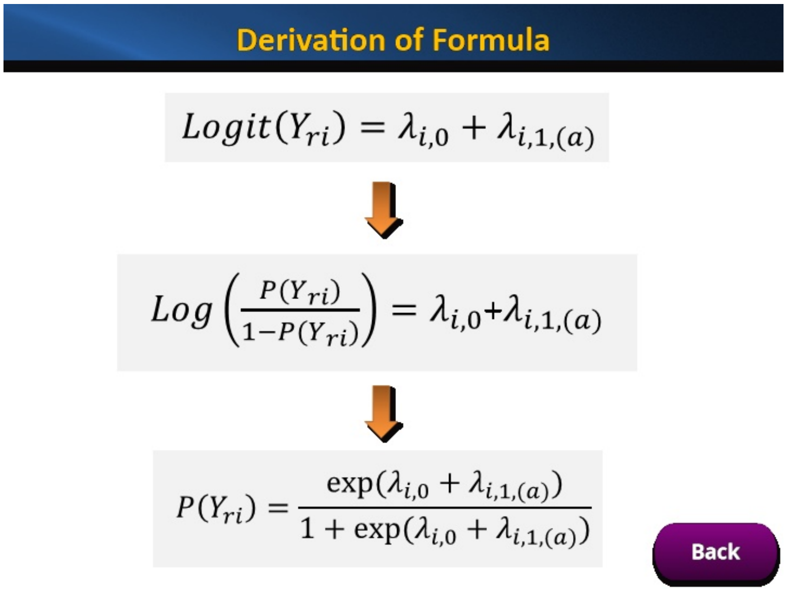
Enter the main effect parameter estimate into the following formula using **Excel**, which is the **conversion of the logit into a probability**:

exp('intercept' + 'main effect') /
[1 + exp('intercept' + 'main effect')]

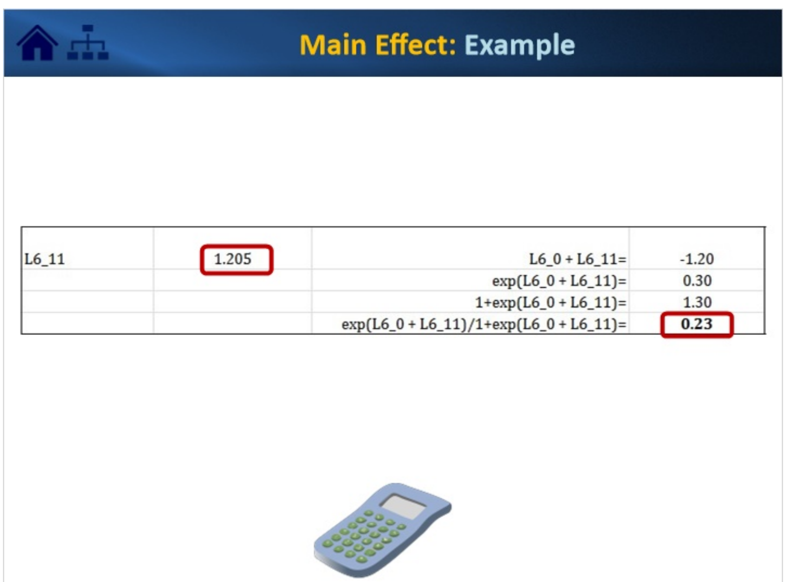
Perform this calculation for **all main effect parameters**, regardless of whether or not the estimate is **statistically significant**

Formula Derivation

Derivation (Slide Layer)

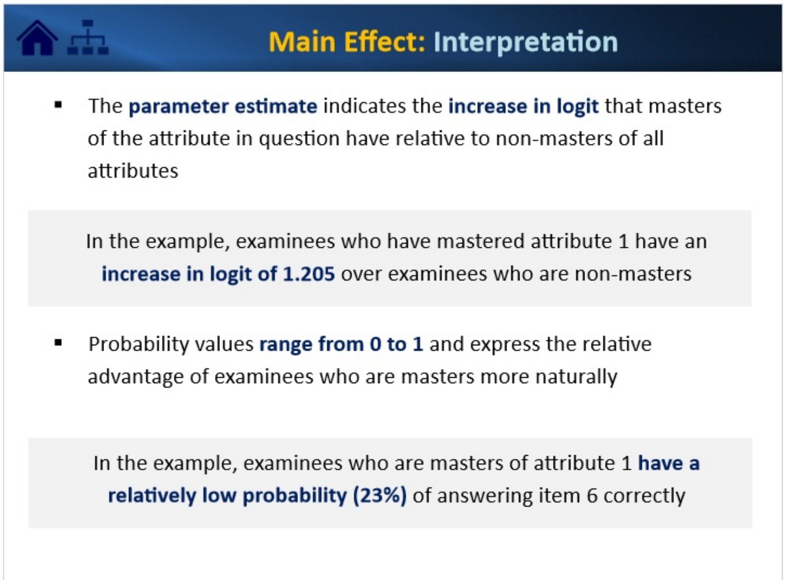


6.62 Main Effect: Example

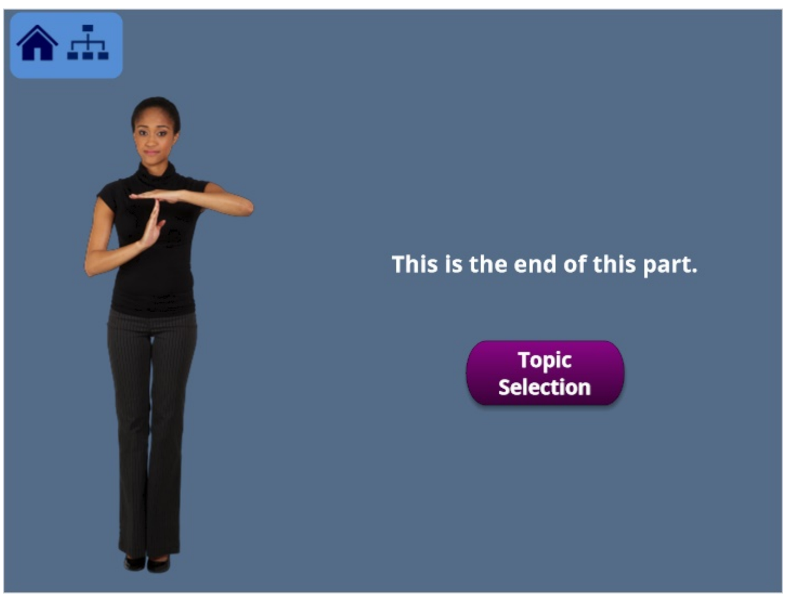


L6_11	1.205	L6_0 + L6_11=	-1.20
		exp(L6_0 + L6_11)=	0.30
		1+exp(L6_0 + L6_11)=	1.30
		exp(L6_0 + L6_11)/1+exp(L6_0 + L6_11)=	**0.23**

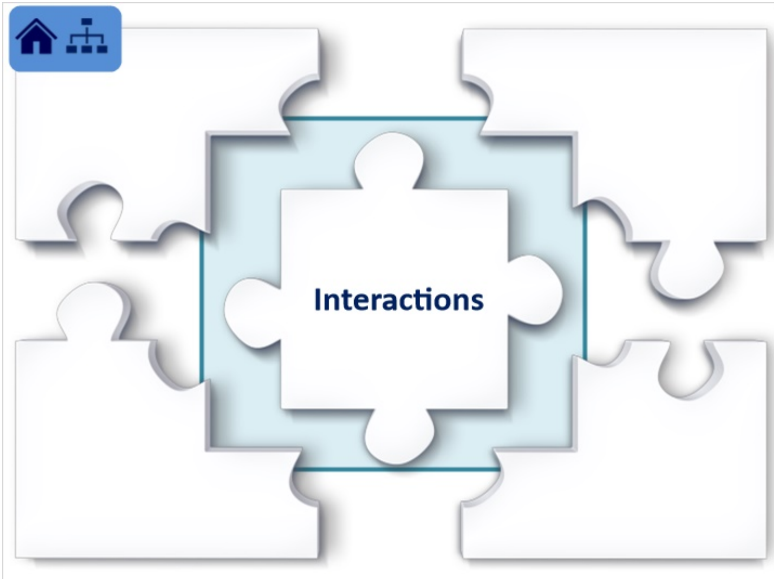
6.63 Main Effect: Interpretation



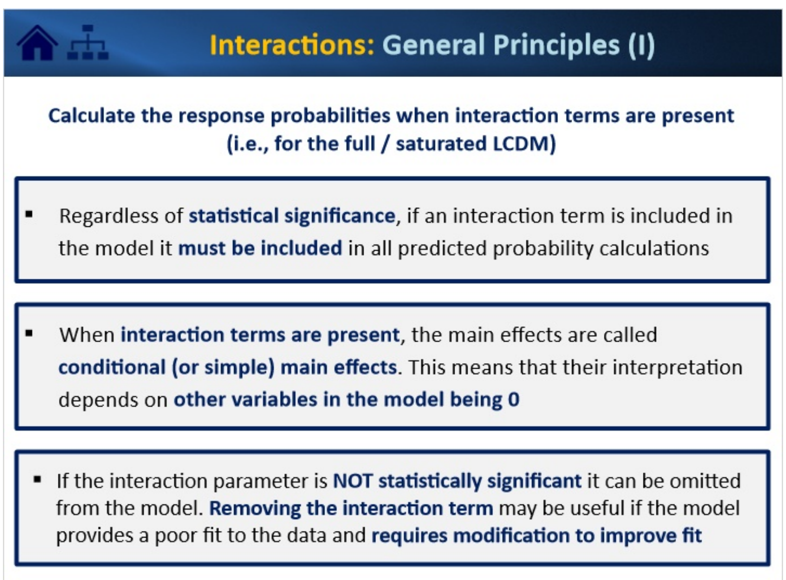
6.64 Bookend: Models without Interaction



6.65 Bookmark: Interactions



6.66 Interactions: General Principles (I)



6.67 Interactions: General Principles (II)

Interactions: General Principles (II)

- An interaction term is an **over-additive** or an **under-additive** effect

- If the interaction parameter estimate is **negative**, there is an **under-additive effect** of mastering both attributes

  mastery of one attribute is sufficient to have a high chance of answering the item correctly

- If the raw interaction parameter estimate is **positive**, there is an **over-additive effect** of mastering both attributes

  there is a "bonus" for mastery of both attributes

6.68 All Parameters: Computational Steps (I)

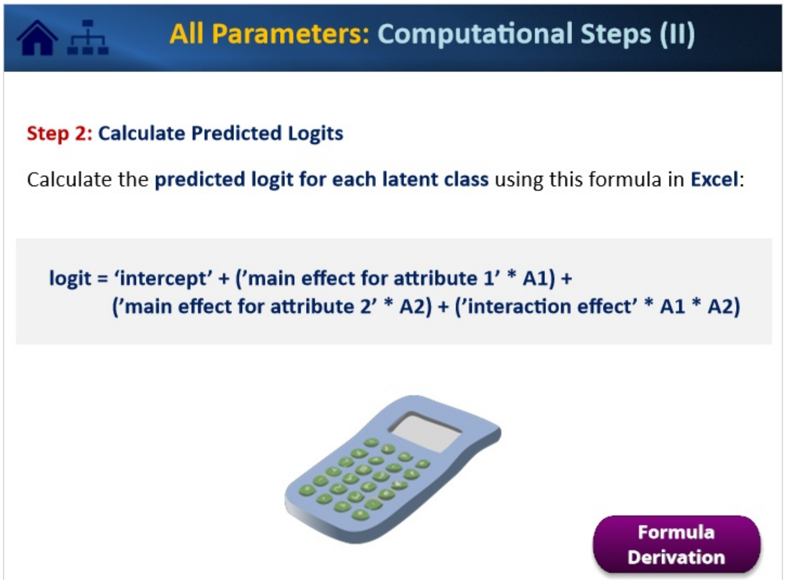
All Parameters: Computational Steps (I)

Step 1: Identify Relevant Parameters

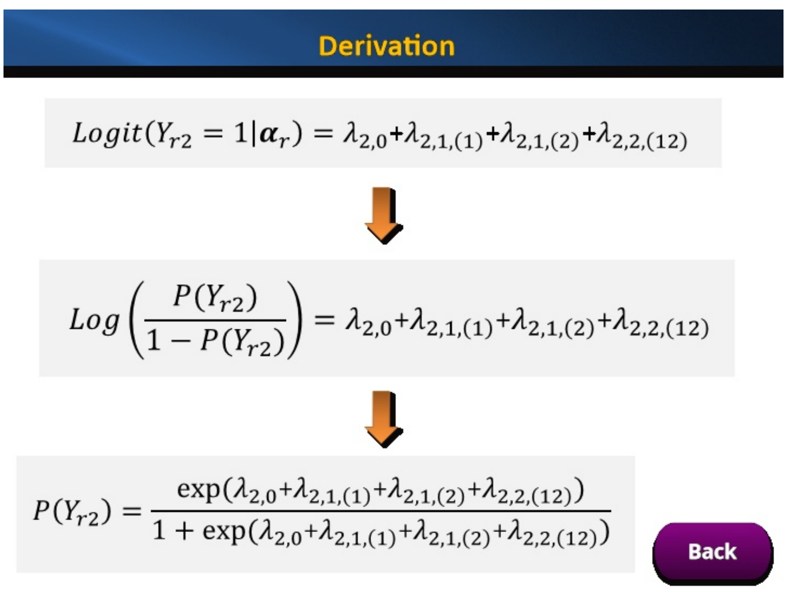
Retrieve the raw intercept, main effect and interaction parameter estimates for each item from the **'New / Additional Parameters'** section of the **Mplus output**:

		Estimate
	New/Additional Parameters	
Intercept	L2_0	0.632
Main Effects	L2_11	2.611
	L2_12	0.725
Interaction Effect	L2_212	0.175

6.69 All Parameters: Computational Steps (II)



Derivation (Slide Layer)



6.70 All Parameters: Example (I)

All Parameters: Example (I)

Class [A1, A2]	Calculation: Intercept		Main Effect for A1		Main Effect for A2		A1*A2 interaction	Logit
Class 1 [0,0]:	0.632	+	(2.611*0)	+	(0.725*0)	+	(0.175*0*0)	**0.632**
Class 2 [1,0]:	0.632	+	(2.611*1)	+	(0.725*0)	+	(0.175*1*0)	**3.243**
Class 3 [0,1]:	0.632	+	(2.611*0)	+	(0.725*1)	+	(0.175*0*1)	**1.357**
Class 4 [1,1]:	0.632	+	(2.611*1)	+	(0.725*1)	+	(0.175*1*1)	**4.143**

6.71 All Parameters: Computational Steps (III)

All Parameters: Computational Steps (III)

Step 3: Calculate Predicted Response Probabilities

Convert each of the predicted logits into predicted response probabilities using the following formula:

exp('logit')/[1+exp('logit')]

logit = 'intercept' + ('main effect for attribute 1' * A1) + ('main effect for attribute 2' * A2) + ('interaction effect' * A1 * A2)

Formula Derivation

Derivation (Slide Layer)

Derivation

$$Logit(Y_{r2} = 1|\boldsymbol{\alpha}_r) = \lambda_{2,0}+\lambda_{2,1,(1)}+\lambda_{2,1,(2)}+\lambda_{2,2,(12)}$$

$$Log\left(\frac{P(Y_{r2})}{1-P(Y_{r2})}\right) = \lambda_{2,0}+\lambda_{2,1,(1)}+\lambda_{2,1,(2)}+\lambda_{2,2,(12)}$$

$$P(Y_{r2}) = \frac{\exp(\lambda_{2,0}+\lambda_{2,1,(1)}+\lambda_{2,1,(2)}+\lambda_{2,2,(12)})}{1+\exp(\lambda_{2,0}+\lambda_{2,1,(1)}+\lambda_{2,1,(2)}+\lambda_{2,2,(12)})}$$

Back

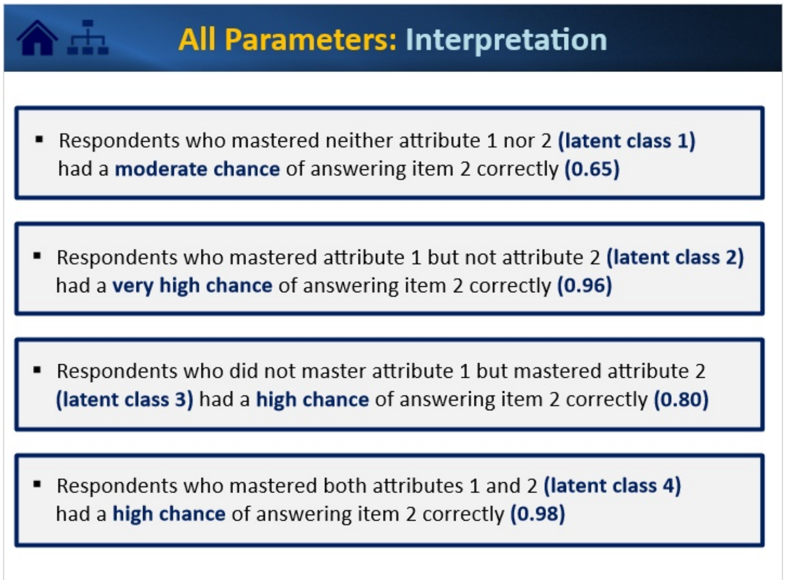
6.72 All Parameters: Example (II)

All Parameters: Example (II)

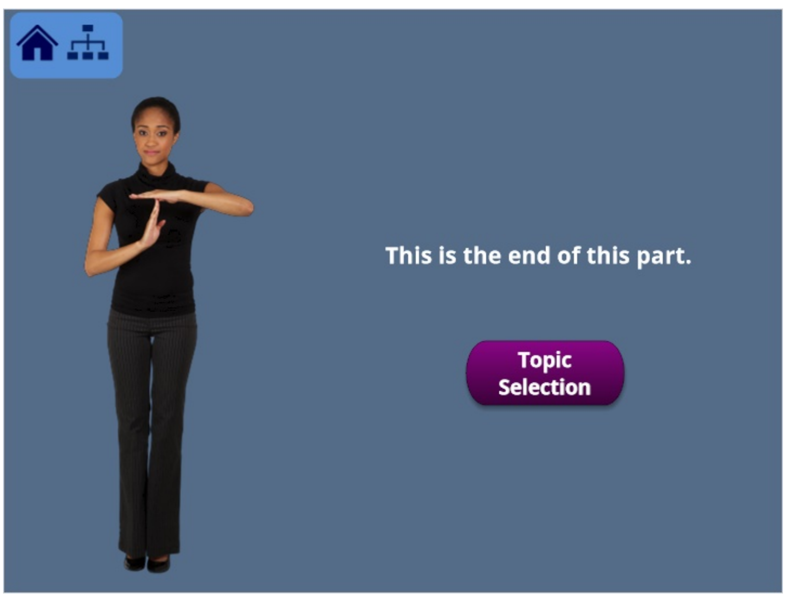
exp(logit) [1+exp(logit)]

Class [A1, A2]	Calculation				Probability
Class 1 [0,0]:	exp(0.632)	/	(1+exp(0.632))	=	0.65
Class 2 [1,0]:	exp(3.243)	/	(1+exp(3.243))	=	0.96
Class 3 [0,1]:	exp(1.357)	/	(1+exp(1.357))	=	0.80
Class 4 [1,1]:	exp(4.143)	/	(1+exp(4.143))	=	0.98

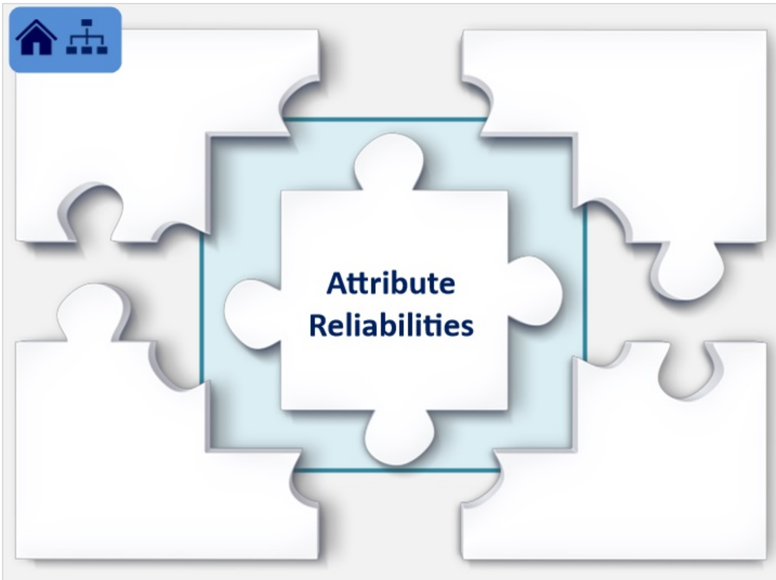
6.73 All Parameters: Interpretation



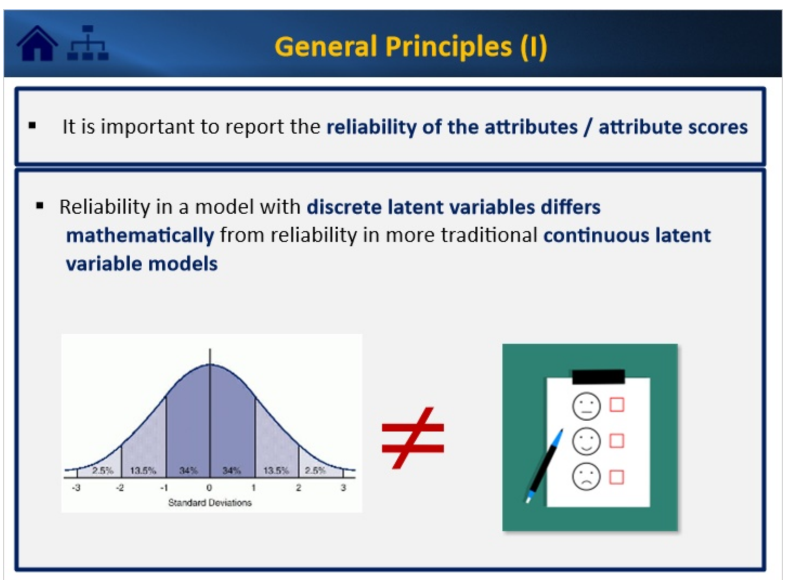
6.74 Bookend: Models with Interaction



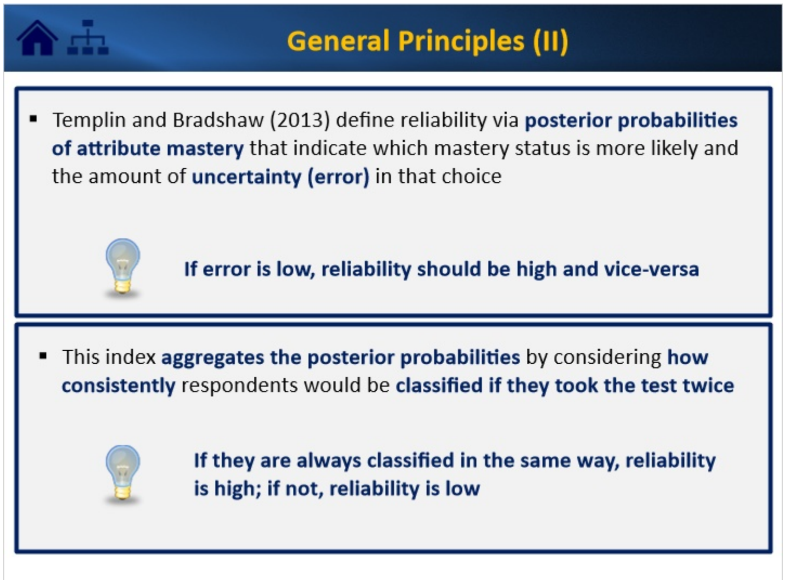
6.75 Bookmark: Reliability



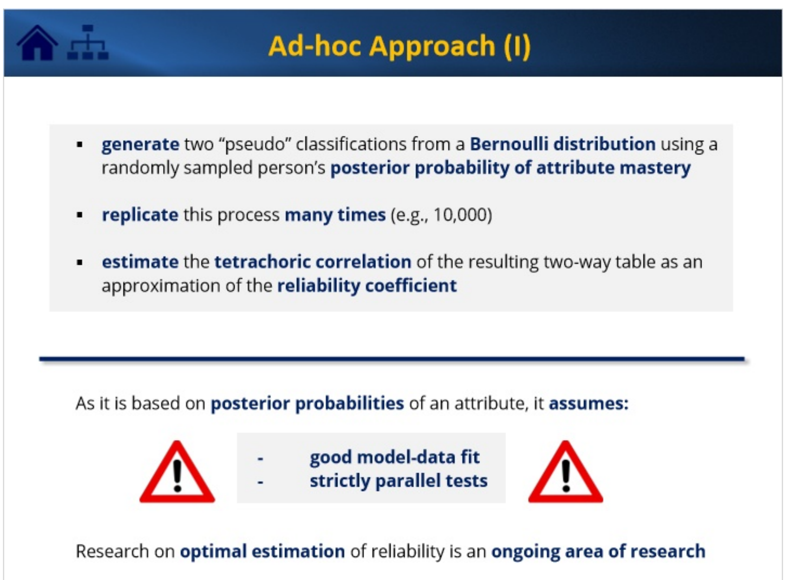
6.76 General Principles (I)



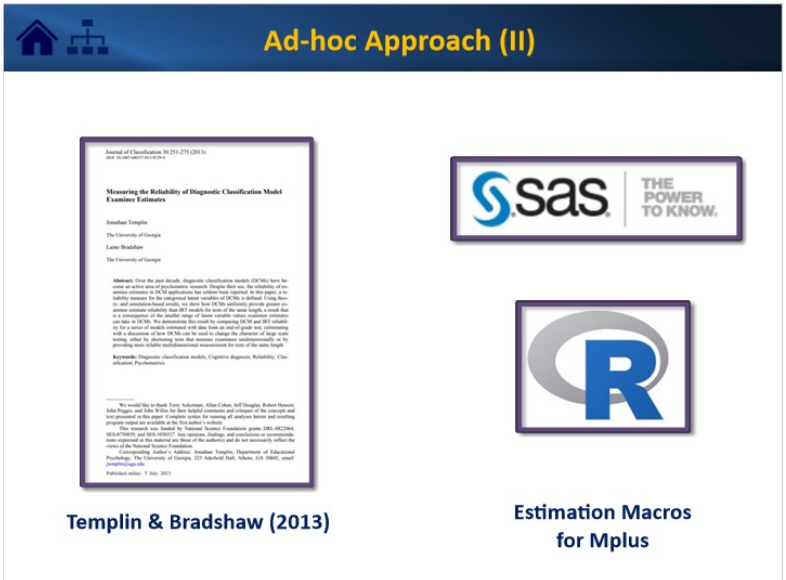
6.77 General Principles (II)



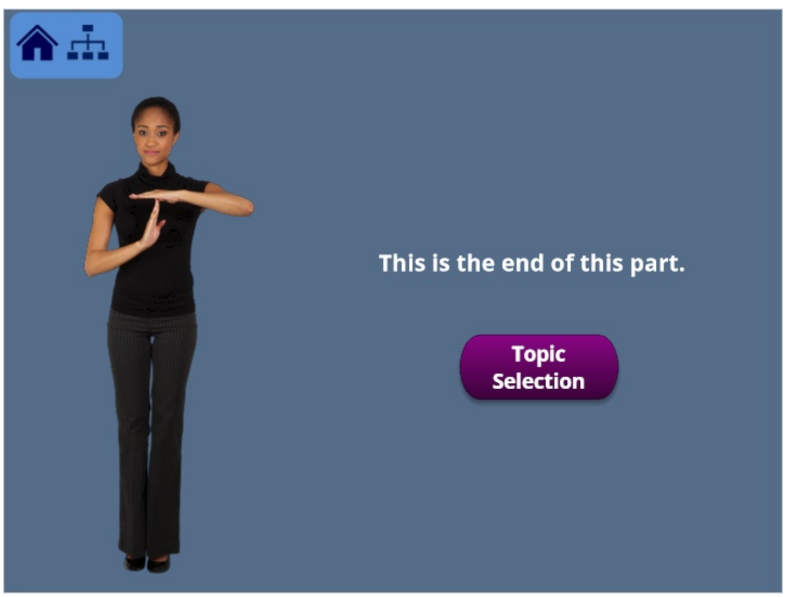
6.78 Ad-hoc Approach (I)



6.79 Ad-hoc Approach (II)

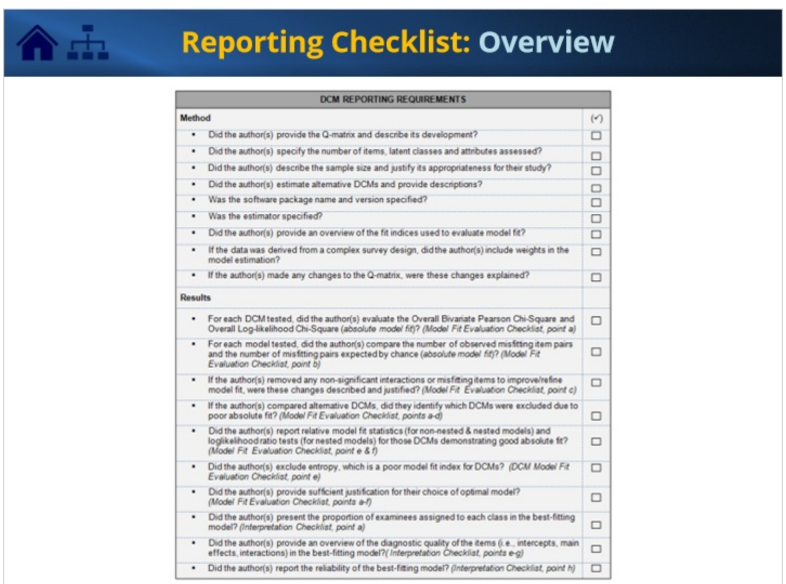


6.80 Bookend: Reliability



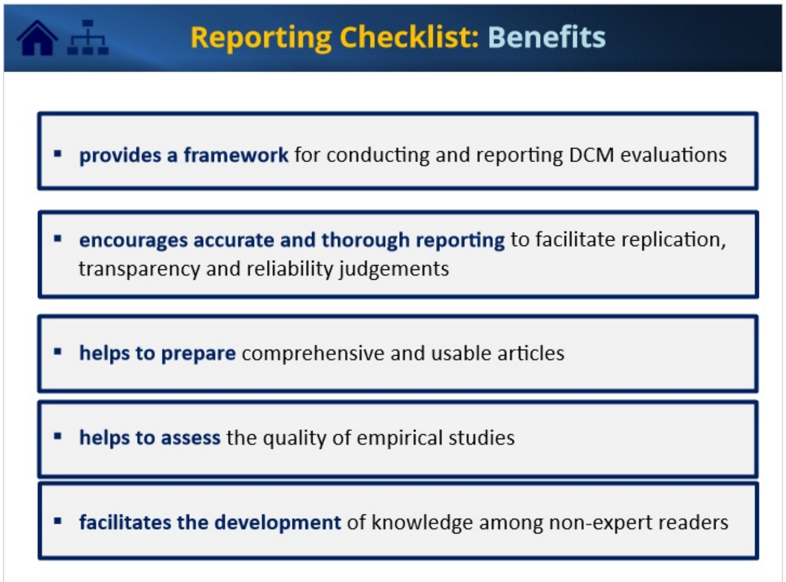
6.81 Bookmark: Reporting Checklist

6.82 Reporting



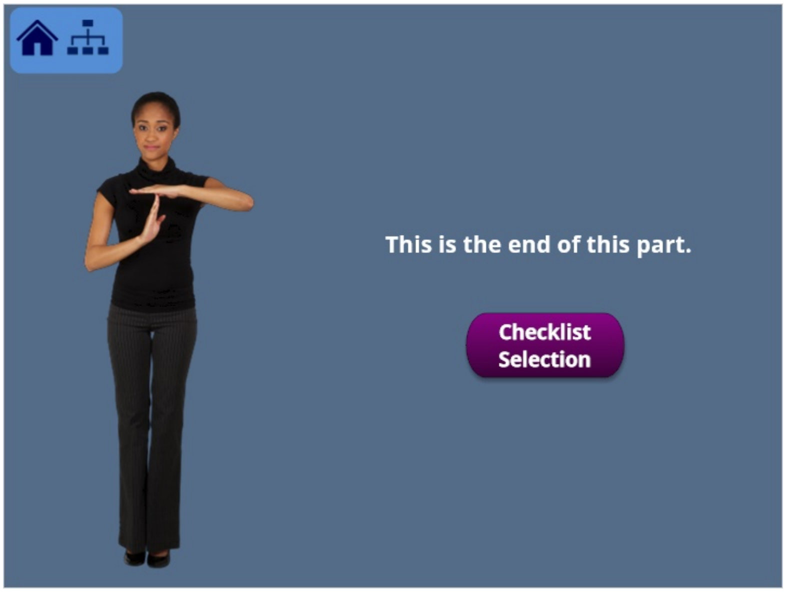
DCM REPORTING REQUIREMENTS	
Method	(✓)
• Did the author(s) provide the Q-matrix and describe its development?	☐
• Did the author(s) specify the number of items, latent classes and attributes assessed?	☐
• Did the author(s) describe the sample size and justify its appropriateness for their study?	☐
• Did the author(s) estimate alternative DCMs and provide descriptions?	☐
• Was the software package name and version specified?	☐
• Was the estimator specified?	☐
• Did the author(s) provide an overview of the fit indices used to evaluate model fit?	☐
• If the data was derived from a complex survey design, did the author(s) include weights in the model estimation?	☐
• If the author(s) made any changes to the Q-matrix, were these changes explained?	☐
Results	
• For each DCM tested, did the author(s) evaluate the Overall Bivariate Pearson Chi-Square and Overall Log-likelihood Chi-Square (*absolute model fit*)? *(Model Fit Evaluation Checklist, point a)*	☐
• For each model tested, did the author(s) compare the number of observed misfitting item pairs and the number of misfitting pairs expected by chance (*absolute model fit*)? *(Model Fit Evaluation Checklist, point b)*	☐
• If the author(s) removed any non-significant interactions or misfitting items to improve/refine model fit, were these changes described and justified? *(Model Fit Evaluation Checklist, point c)*	☐
• If the author(s) compared alternative DCMs, did they identify which DCMs were excluded due to poor absolute fit? *(Model Fit Evaluation Checklist, points a-d)*	☐
• Did the author(s) report relative model fit statistics (for non-nested & nested models) and loglikelihood ratio tests (for nested models) for those DCMs demonstrating good absolute fit? *(Model Fit Evaluation Checklist, point e & f)*	☐
• Did the author(s) exclude entropy, which is a poor model fit index for DCMs? *(DCM Model Fit Evaluation Checklist, point e)*	☐
• Did the author(s) provide sufficient justification for their choice of optimal model? *(Model Fit Evaluation Checklist, points a-f)*	☐
• Did the author(s) present the proportion of examinees assigned to each class in the best-fitting model? *(Interpretation Checklist, point a)*	☐
• Did the author(s) provide an overview of the diagnostic quality of the items (i.e., intercepts, main effects, interactions) in the best-fitting model?*(Interpretation Checklist, points e-g)*	☐
• Did the author(s) report the reliability of the best-fitting model? *(Interpretation Checklist, point h)*	☐

6.83 Reporting Checklist Benefits

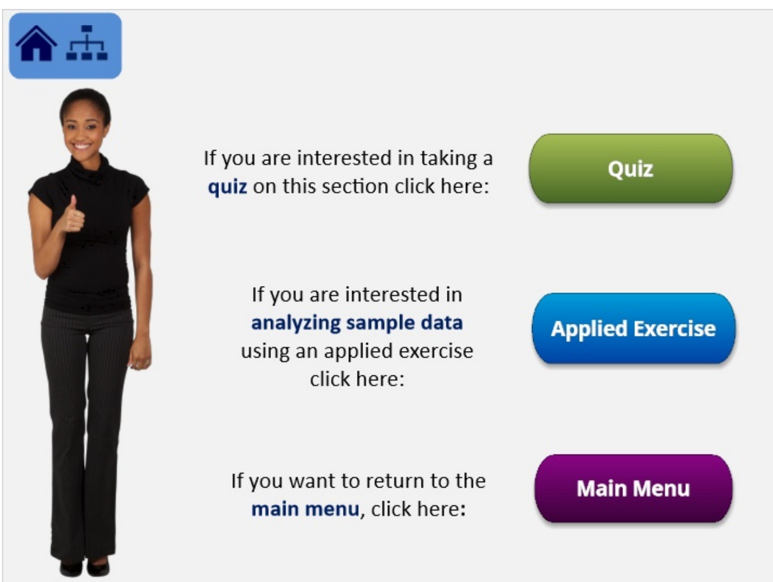


6.84 Reporting Checklists in other fields

6.85 Bookend: Reporting Checklist



6.86 Bookend: Section 5



6.87 Module Cover (END)