Analyzing Longitudinal Changes in Mental health: Integrating variable-centered and person-centered approaches

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What are we going to discuss today?

1. Variable- and person-centered approaches
2. An approach which integrates variable- and person-centered approaches: Growth mixture modeling (GMM)
3. An overview of considerations and steps in running GMM

1. Variable- and person-centered approaches

Variable-Centered Approaches

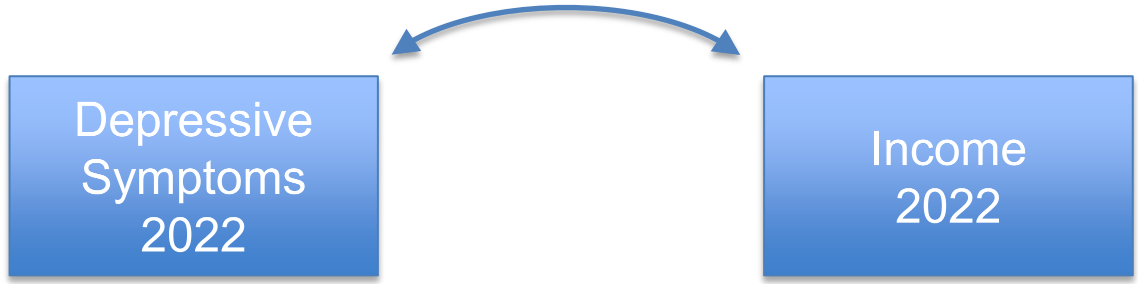
- Variable-centered approaches to data
- Widely employed in many disciplines
- Focus on variables
  - e.g., correlation analysis, regression, latent growth curve modeling

Variable-Centered Approaches

Example 1

How does depressive symptoms associate with income concurrently?

- Correlation



Variable-Centered Approaches

Example 2

How does depressive symptoms change over time?

Depressive Symptoms 2020

Depressive Symptoms 2021

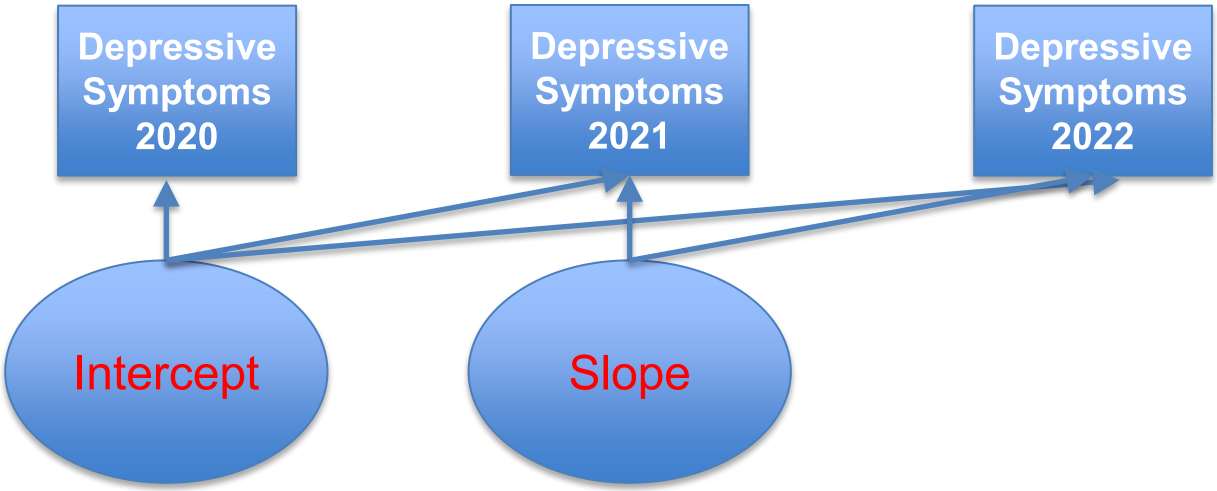
Depressive Symptoms 2022

Variable-Centered Approaches

Example 2

How does depressive symptoms change over time?

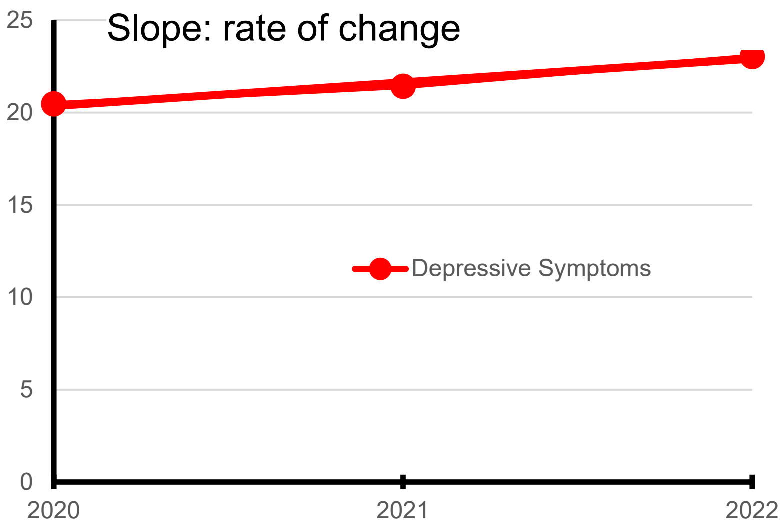
- Latent growth curve modeling
  - Slope (rate of change) and Intercept

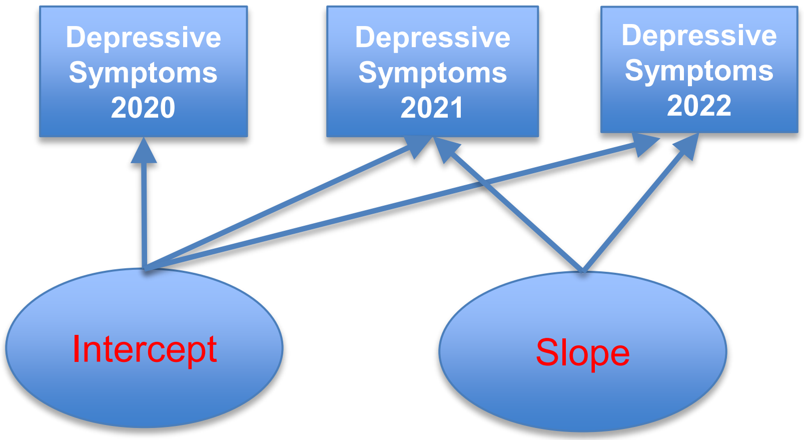


Variable-Centered Approaches

Example 2

How does depressive symptoms change over time?



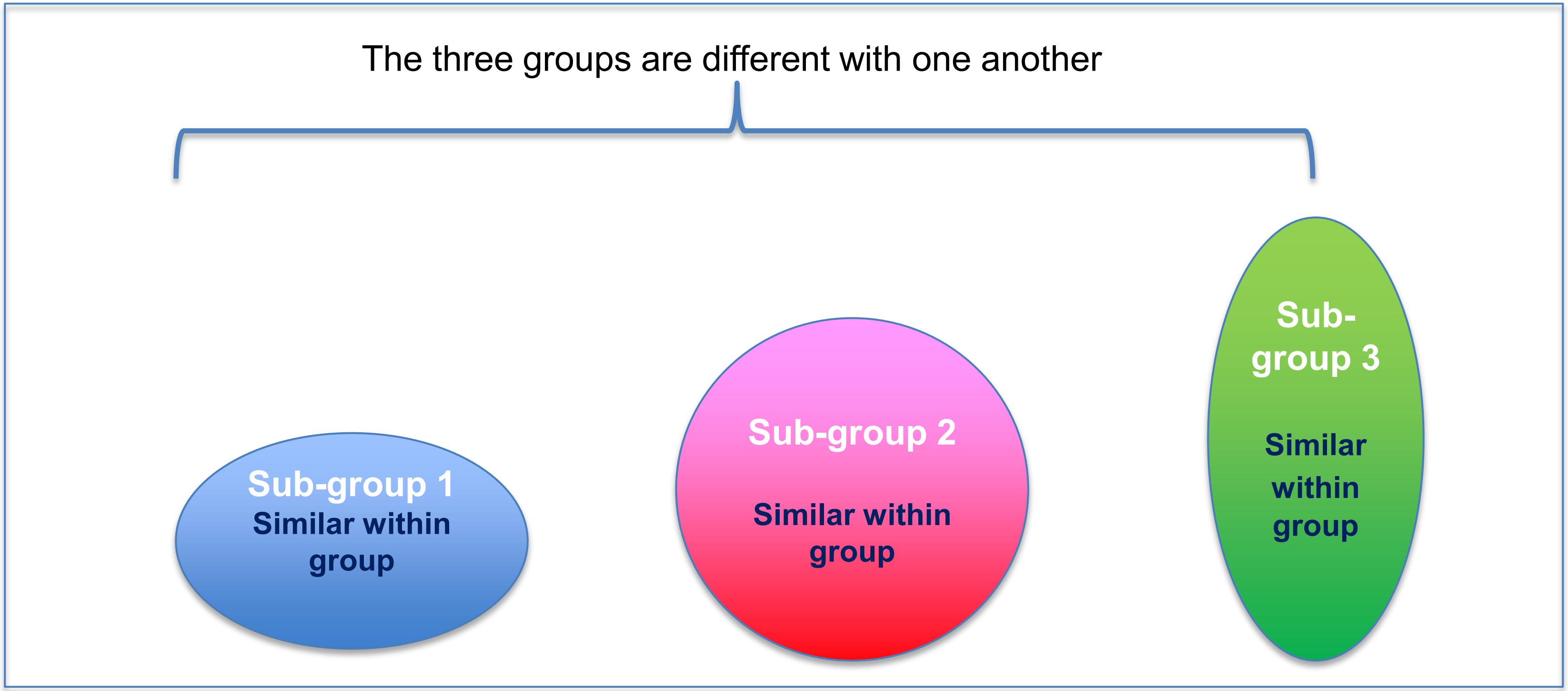


Person-Centered Approaches

- Person-centered approaches to data
- Focus on person
  - e.g., k-means cluster analysis, latent profile analysis
    - Identify sub-groups of individuals (identify more homogeneous smaller groups within the larger heterogeneous group)

Person-Centered Approaches

- identify more homogeneous smaller groups in the larger heterogeneous group)



Person-Centered Approaches

- Example: Lee et al., 2014
  - Subtypes of Depressive Symptoms
  - Latent class analysis
  - Sample: N = 13424

    from 2001 -2002 National Epidemiological Survey of Alcohol and Related Conditions (NESARC) data

Person-Centered Approaches

- Example: Lee et al., 2014
  - Depressive Symptoms items:
    a) Increasing/decreasing of weight
    b) Difficulty in falling asleep/oversleeping
    c) Fatigue
    d) Psychomotor difficulty
    e) Concentration/decision making difficulty
    f) Excessive feelings of worthlessness/guilt
    g) Thoughts of death or suicide

Person-Centered Approaches

- Example: Lee et al., 2014
  - Latent class analysis identified 4 subgroups:
    1) *Mild* subgroup (lower probabilities of all depressive symptoms)
    2) *Cognitive* subgroup (high probabilities of worthlessness and concentration difficulties)
    3) *Psychosomatic* subgroup (i.e., high probabilities of sleeping problems, fatigue, and impaired concentration)
    4) *Severe* subgroup (i.e., high probabilities of all depressive symptoms)
  - Follow-up analysis: Mental health service use of these 4 depressive subtypes

2. An approach which integrates variable- and person-centered approaches: Growth Mixture Modeling

A longitudinal study of maternal depressive symptoms as example (Chow et. al, 2019)

Growth Mixture Modeling

- Example: Chow et. al, 2019
  - Identify the sub-groups of trajectories in maternal depressive symptoms
  - N = 3307 (Canadian mothers)
  - 6 waves of data:
    1. 27 weeks gestation
    2. 36 weeks gestation
    3. 6 months postpartum
    4. 12 months postpartum
    5. 18 months postpartum
    6. 24 months postpartum

Growth Mixture Modeling

- Example: Chow et. al, 2019
  - Depressive symptoms measured by
    - Center for Epidemiologic Studies Depression Scale (CES-D)
    - 20 items; e.g., “felt lonely” “talked less than usual” (in the past week)
    - Response: 0 (none; < 1 day) to 3 (most or all of the time; 5-7 days)
    - Responses were summed (CES-D scores)

Growth Mixture Modeling

- Example: Chow et. al, 2019
  - Growth Mixture Modeling to identify the sub-groups of trajectories in maternal depressive symptoms
  - Integrating variable- and person-centered approaches

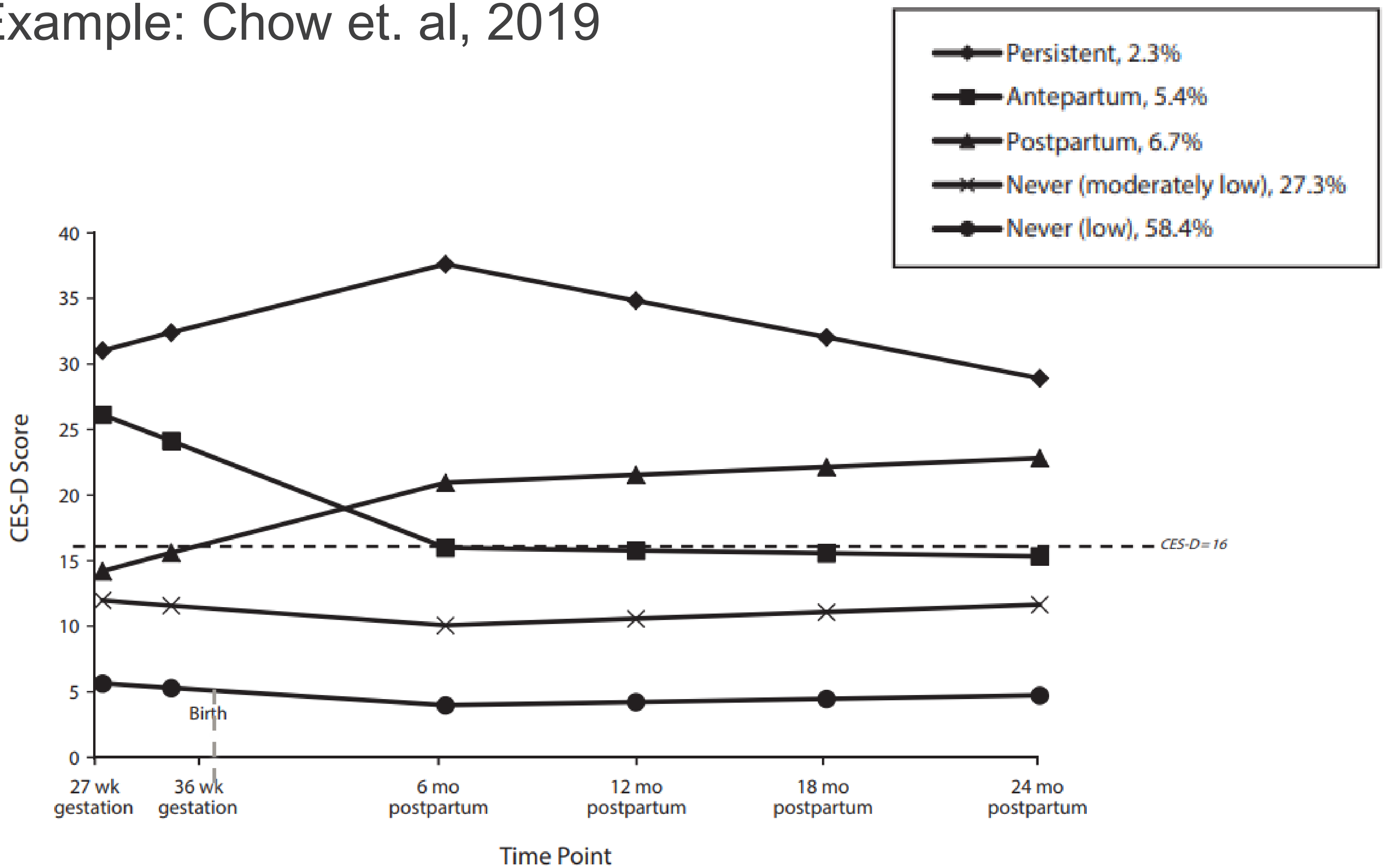
Person-centered

Variable-centered

Sub-Groups of Trajectories

Growth Mixture Modeling

- Example: Chow et. al, 2019



3. An overview of considerations and steps in running growth mixture modeling

Considerations and Steps Running GMM

- Example: Chow et. al, 2019
    - GMM using M*plus*

Step 1: Reliability of CES-D scores

Step 2: Check longitudinal measurement invariance (make sure the instrument is interpreted in the same way over time)

Considerations and Steps Running GMM

Step 3: Latent growth curve model (average trajectory of the whole sample)

- 6 waves of data; identify model specifications:

  Option 1: one linear slope

  Option 2: one linear slope + one quadratic term (i.e. curvilinear trajectory)

  Option 3: piecewise model (with more than 1 slope)

  Consideration based on:

  (1) Model fit (e.g., RMSEA ≤ 0.08, CFI ≥ 0.95)

  (2) Empirical comparison across different options

  (3) Theoretically and contextually appropriate?

Considerations and Steps Running GMM

Step 3: Latent growth curve model (average trajectory of the whole sample)

Table : Fit Indices of the Latent Growth Curve Models for Depressive Symptoms .

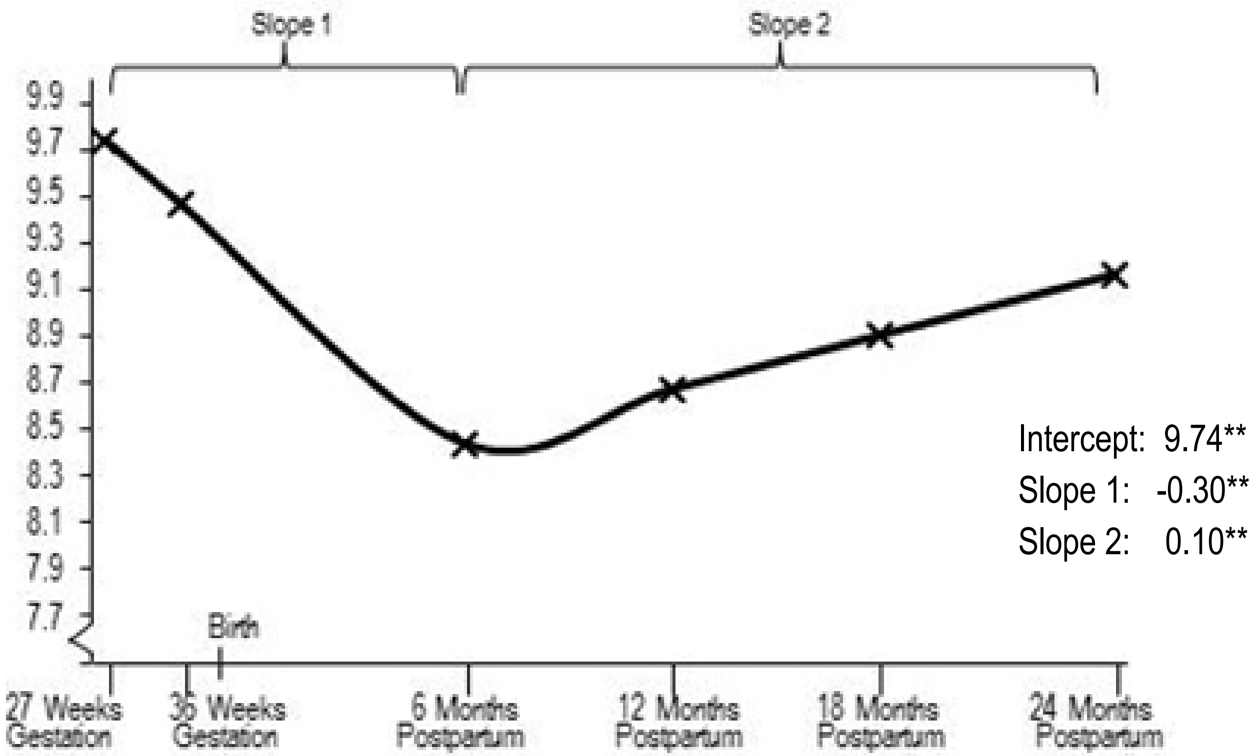
	Model Fit					Means		
	χ^2	df	RMSEA	CFI		I	S1	S2
Model A: One-slope model	146.69**	16	0.05	0.96		9.47**	-0.06**	---
Model B: Two-slope model	50.42**	12	0.03	0.99		9.74**	-0.30**	0.10**

**$p < .01$

The two-slope latent growth curve (LGC) model significantly fit the data better than the basic LGC model (comparison between the two models for depressive symptoms: χ^2_{diff} = 96.27, df_{diff} = 4, p < .01)

Considerations and Steps Running GMM

Step 3: Latent growth curve model (average trajectory of the whole sample)



Considerations and Steps Running GMM

Step 4: After determine the model specifications, check if the variances of the growth factors (i.e., intercept and slope) are significant.

Table : Variances of the Latent Growth Curve Models for Depressive Symptoms .

	Means			Variances		
	I	S1	S2	I	S1	S2
Model B: Two-slope model	9.74**	-0.30**	0.10**	42.42**	0.87**	0.33**

**$p < .01$

Considerations and Steps Running GMM

Step 5 : Identify the optimal solution

- Running GMM is an exploratory process
  - First, run a series of models with different number of classes (sub-groups)
  - Then, identify the "optimal" model (solution), based on

    (a) model indices and some quantitative criteria (more next slide)

    (b) Interpretability of the sub-groups

Considerations and Steps Running GMM

Step 5 : Identify the optimal solution

- Identify the “optimal” model (solution)

  (a) model indices and some quantitative criteria

  - AIC and BIC indices (the smaller the better)’
  - Entropy (the larger the better)
  - pBLRT (*p* values for the bootstrap likelihood ratio test for *K* versus *K*-1 classes)
  - the size of the smallest group should at least exceed 5% of the sample

Considerations and Steps Running GMM

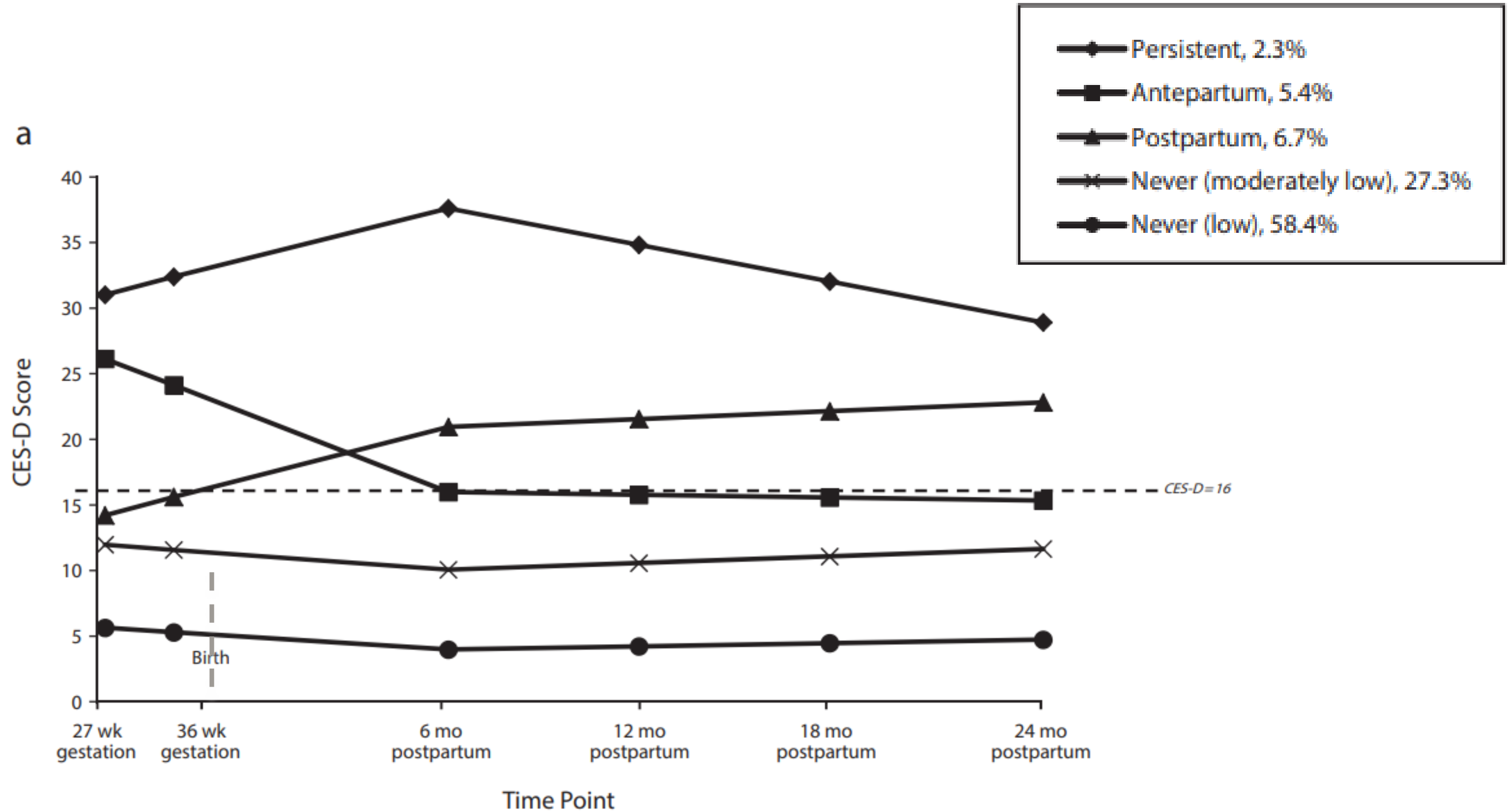
Step 5 : Identify the optimal solution

For example, a researcher run 7 models ranging from 1-class solution to 7-class solution

No. of Sub-Group(s)	AIC	BIC	pBLRT	Entropy
1	109554.00	109608.94	–	
2	104089.60	104168.94	0.00	0.90
3	102643.97	102747.74	0.00	0.88
4	101927.35	102055.53	0.00	0.83
5	101446.94	101599.54	0.00	0.84
6	101369.39	101656.40	0.19	0.84
7	101108.71	101710.14	0.27	0.84

Considerations and Steps Running GMM

Step 6 : Label the sub-groups (according their characteristics)



Considerations and Steps Running GMM

A very helpful reference to learn more about GMM (with M*plus* Syntax):

Jung, T., & Wickrama, K. A. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and personality psychology compass*, *2*(1), 302-317.

Considerations and Steps Running GMM

Mplus - [2CLASS]

File Edit View Mplus Plot Diagram Window Help

```
TITLE: GGM Example

DATA:
File = C:\Users\Angela\007_Mplus\001_17.DAT;

VARIABLE:
NAMES ARE ID W1 W2 W3;

MISSING ARE all(999);

USEVAR =   W1 W2 W3;

IDVARIABLE = ID;

CLASSES = c(2);


ANALYSIS:
  TYPE = MIXTURE;
  STARTS = 500 20;


MODEL:
%OVERALL%
I S| W1@0 W2@1 W3@2;


OUTPUT:
SAMPSTAT STANDARDIZED MODINDICES tech4;
```

Discussion

- You may consider doing more analysis after GMM
  - Example: Chow et. al, 2019
  - We used multinomial logistic regression
    - to test how group membership was associated with various risk and protective factors
    - e.g., Immigrants living in Canada for more than 5 up to 10 years, but not more recent arrivals, were at higher risk for persistent depression
    - Possible explanation: recent immigrants exhibit good physical and mental health subsequent to Canada's immigrant selection policy (the healthy immigrant effect)
    - However, these advantages may decline over time as women encounter challenges in their new homeland

Discussion

- You may consider doing more analysis after GMM
  - Example: Chow et. al, 2019
  - We also did another set of GMM on perceived stress and test how the group membership was associated with various risk and protective factors
  - Allow us to explore the similarities and differences of the findings associated with depressive symptoms and perceived stress
    - e.g., people being married had lower odds for persistent perceived stress (but no significant result yield for persistent depressive symptoms)

Discussion

- Select methods and approaches according to research questions

References

Chow, A., Dharma, C., Chen, E., Mandhane, P. J., Turvey, S. E., Elliott, S. J., ... & Kozyrskyj, A. L. (2019). Trajectories of depressive symptoms and perceived stress from pregnancy to the postnatal period among Canadian women: impact of employment and immigration. *American journal of public health*, *109*(S3), S197-S204.

Jung, T., & Wickrama, K. A. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and personality psychology compass*, *2*(1), 302-317.

Lee, S. Y., Xue, Q. L., Spira, A. P., & Lee, H. B. (2014). Racial and ethnic differences in depressive subtypes and access to mental health care in the United States. *Journal of affective disorders*, *155*, 130-137.

Thank You!

Discussion

- You may consider doing more analysis after GMM
  - Example: Chow et. al, 2019
  - We also did another set of GMM on perceived stress
    - examined the associations between the trajectory patterns of depressive symptoms and perceived stress
    - by configural frequency analysis (compares observed and expected frequencies in a cross-tabulation and tests whether cell frequencies are larger or smaller than expected based on chance)