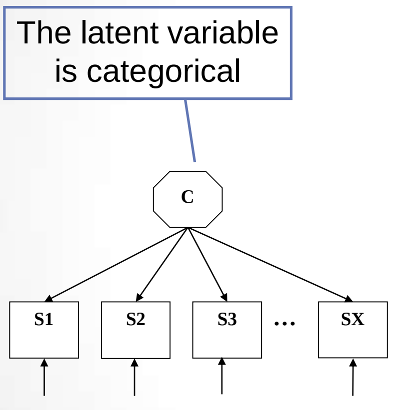
Panel Discussion: Increasing our Analytic Sophistication

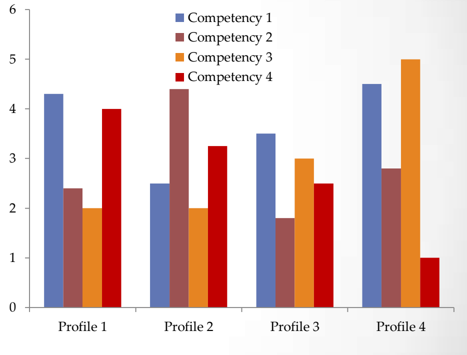
Person-Centered Analyses

Alexandre J.S. Morin, Simon A. Houle, & David Litalien

2017 Conference on Commitment

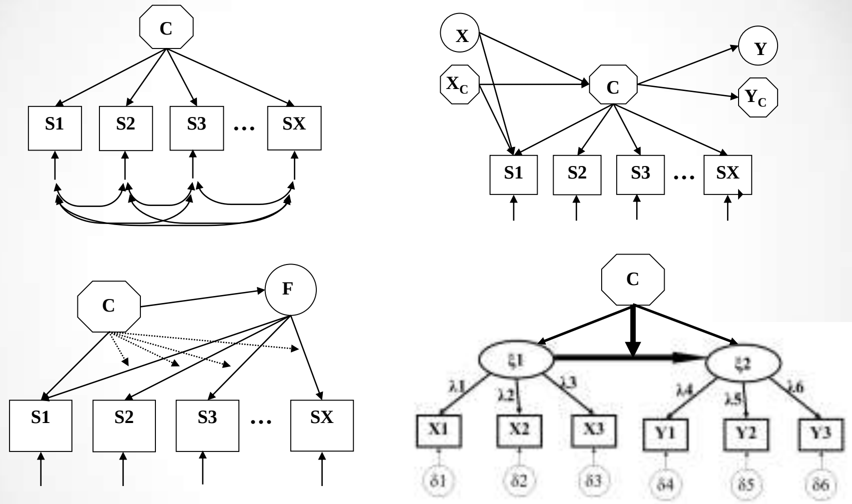
Latent Profile Analysis





$$\sigma_y^2 = \sum_{k=1}^{K} \pi_k (\mu_{yk} - \mu_y)^2 + \sum_{k-1}^{K} \pi_k \sigma_{yk}^2$$

Generalized SEM

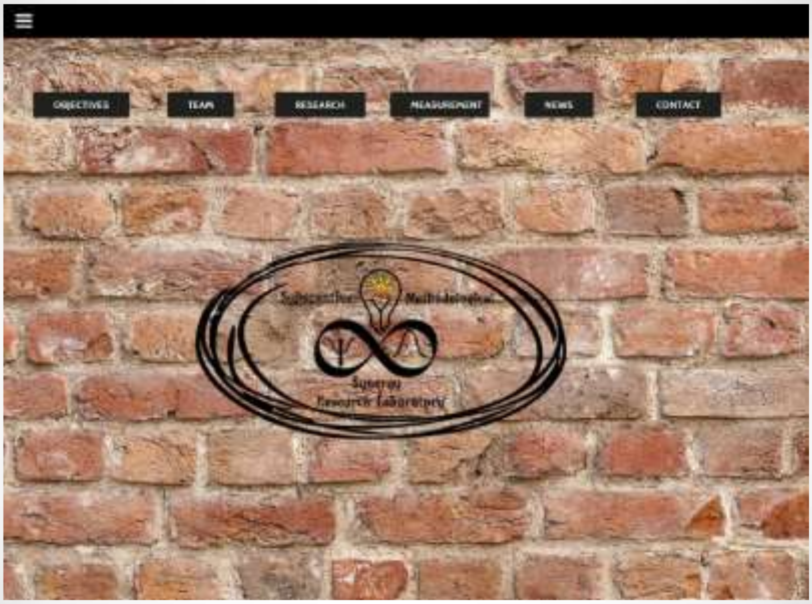


Focus:
Mixture Modeling / Generalized Structural Equation Modeling.

Meyer, J.P., & Morin, A.J.S. (2016). A person-centered approach to commitment research: Theory, research, and methodology. *Journal of Organizational Behavior*, *37*, 584-612.

Morin, A.J.S. (2016). Person-centered research strategies in commitment research. In J.P. Meyer (Ed.), *The Handbook of Employee Commitment* (p. 490-508). Cheltenham, UK: Edward Elgar

Morin, A.J.S., & Wang, J.C.K. (2016). A gentle introduction to mixture modeling using physical fitness data. In N. Ntoumanis, & N. Myers (Eds.), *An Introduction to Intermediate and Advanced Statistical Analyses for Sport and Exercise Scientists* (pp. 183-210). London, UK: Wiley.



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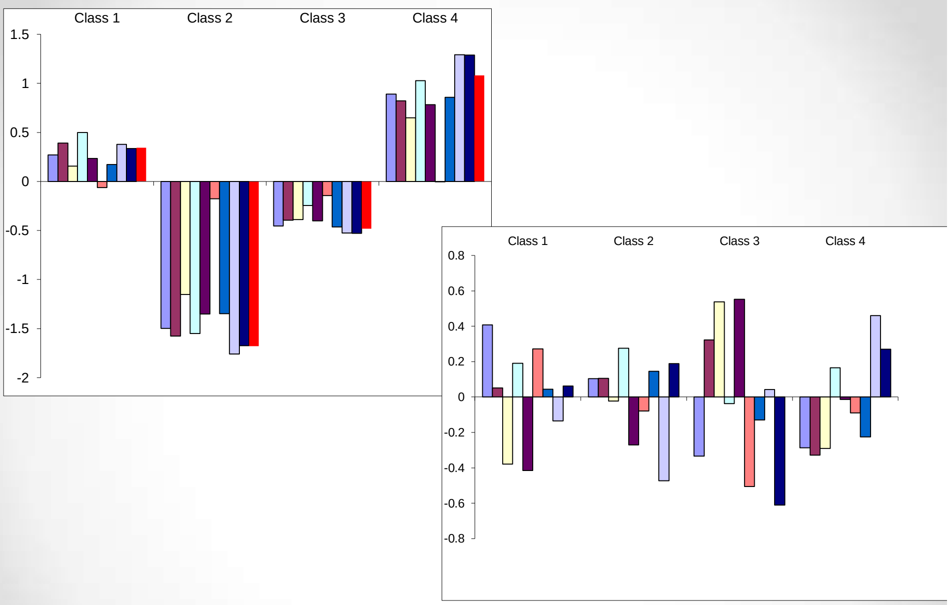
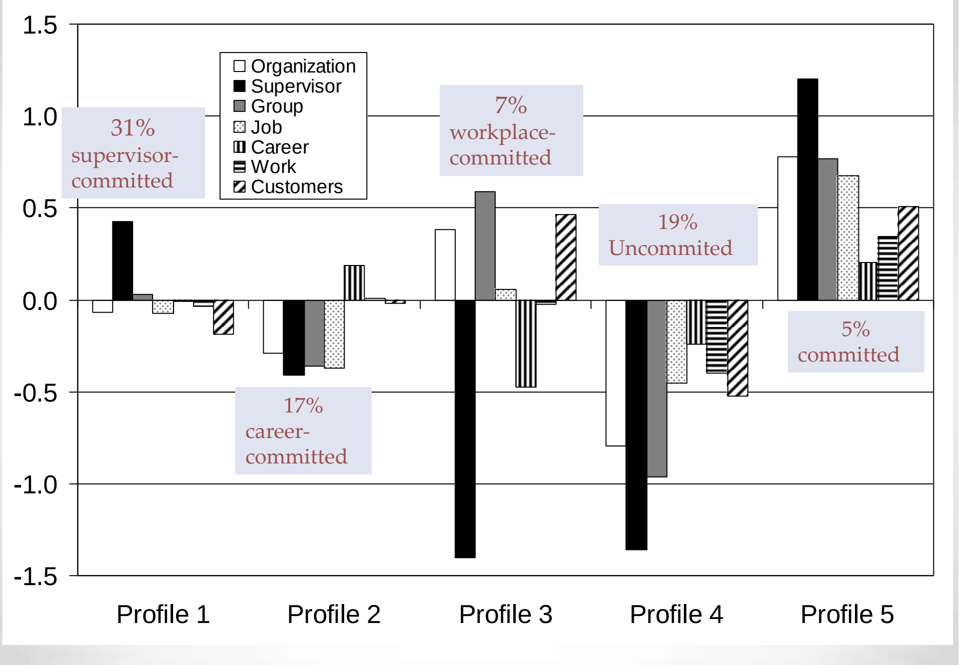
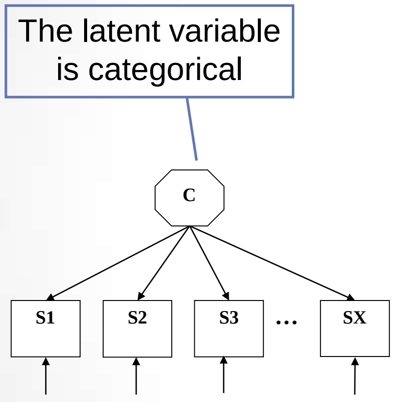
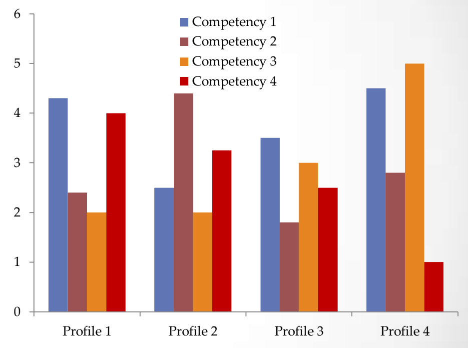


Morin, A.J.S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture Analysis. *Organizational Research Methods, 14* (1), 58-90.



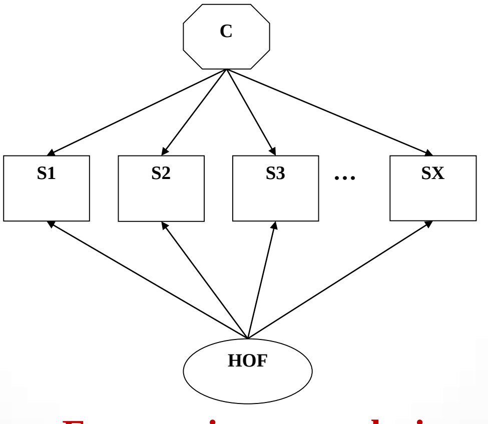
Latent Profile Analysis





$$\sigma_y^2 = \sum_{k=1}^{K} \pi_k (\mu_{yk} - \mu_y)^2 + \sum_{k-1}^{K} \pi_k \sigma_{yk}^2$$

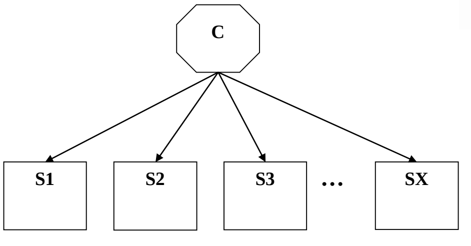
BUT



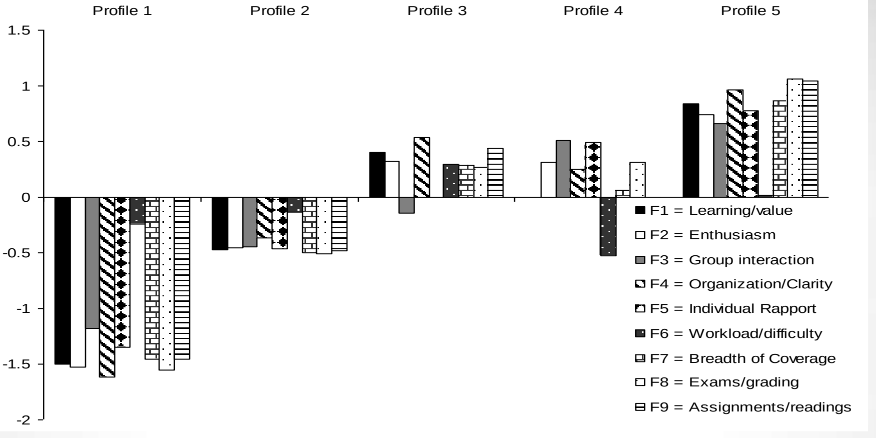
Factor mixture analysis.

Morin, A.J.S., & Marsh, H.W. (2015). Disentangling Shape from Levels Effects in Person-Centred Analyses: An Illustration Based University Teacher Multidimensional Profiles of Effectiveness. *Structural Equation Modeling*, *22*, 39-59.

Model 1

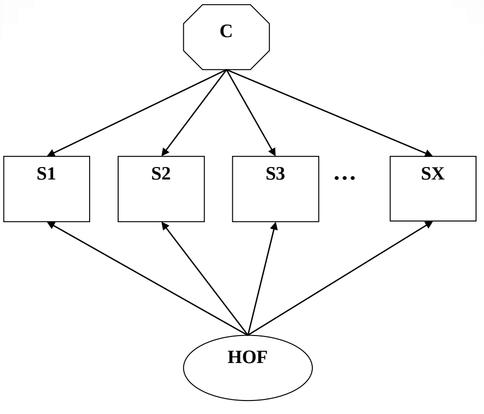


Model 1: Classical latent profile analysis.

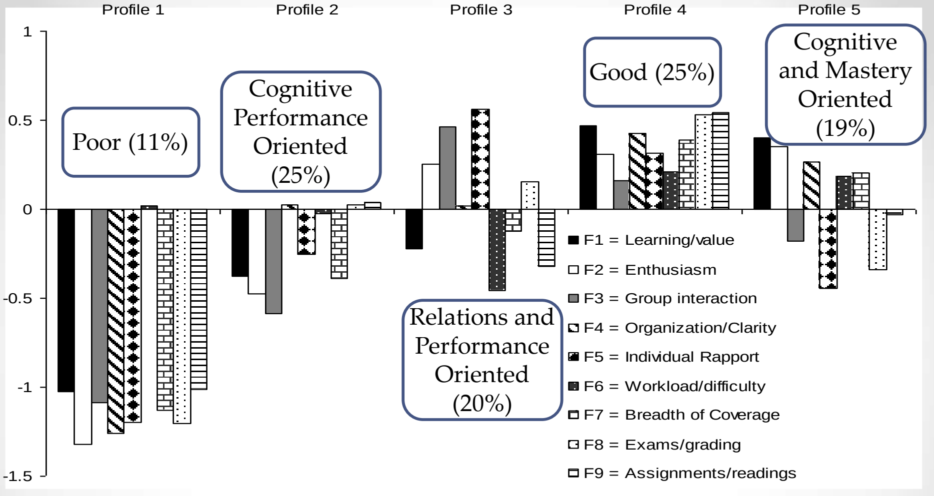


Results from the latent profiles models based on 9 factors (Model 1)

Model 3



Model 3: **Factor mixture analysis** with a class invariant higher order latent factor.



Results from the factor mixture models based on 9 factors (Model 3)

BUT

The Factor Mixture approach also assumes that the mean level on the global factor is equal across all profiles, and corresponds to the sample average.

Scale Scores ?

- What about measurement errors???
- **Why not use factor scores:**
  - Provide a partial control for measurement error
  - Forces you to demonstrate that the measurement model fits the data well.
  - Preserves the nature of the measurement model: invariance, cross loadings, method factors, etc.
  - Naturally standardized.

Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254.

Morin, A.J.S., & Marsh, H.W. (2015). Disentangling Shape from Levels Effects in Person-Centred Analyses: An Illustration Based University Teacher Multidimensional Profiles of Effectiveness. *Structural Equation Modeling*, *22*, 39-59.

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., Madore, I., & Desrumaux, P. (2016). Further reflections on disentangling shape and level effects in person-centered analyses: An illustration aimed at exploring the dimensionality of psychological health. *Structural Equation Modeling*, *23*, 438-454

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., McInerney, D.M., Dagenais-Desmarais, V., & Madore, I. (In Press). Complementary variable- and person-centered approaches to exploring the dimensionality of psychometric constructs: Application to psychological wellbeing at work. *Journal of Business and Psychology*. Early View DOI 10.1007/s10869-016-9448-7

Morin, A.J.S., Boudrias, J.-S., Marsh, H.W., Madore, I., & Desrumaux, P. (2016). Further reflections on disentangling shape and level effects in person-centered analyses: An illustration aimed at exploring the dimensionality of psychological health. *Structural Equation Modeling*, *23*, 438-454

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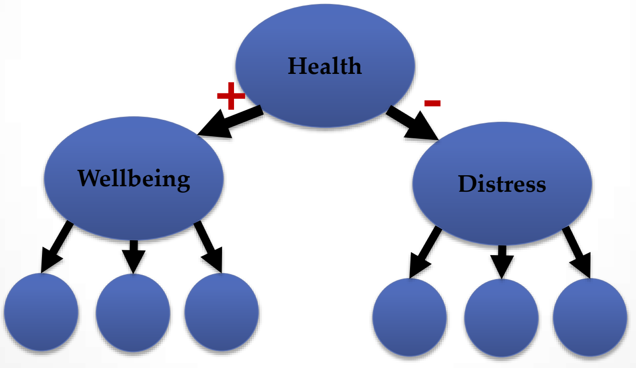
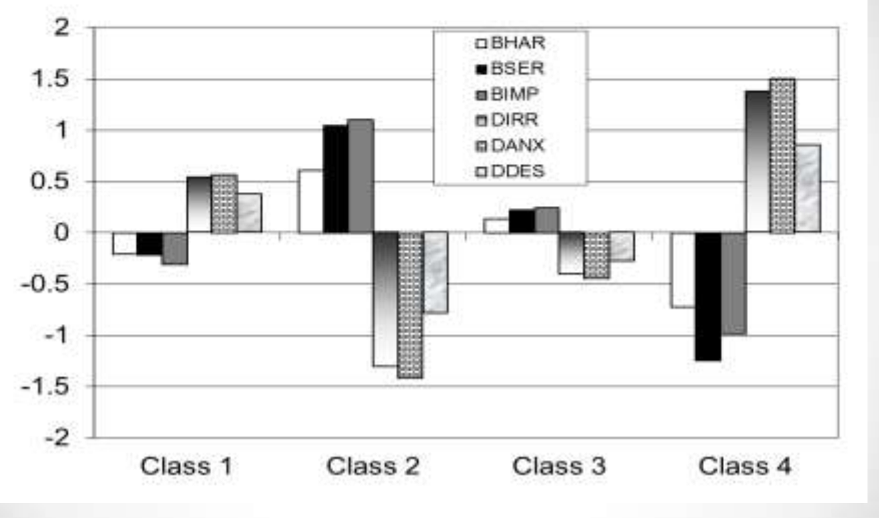
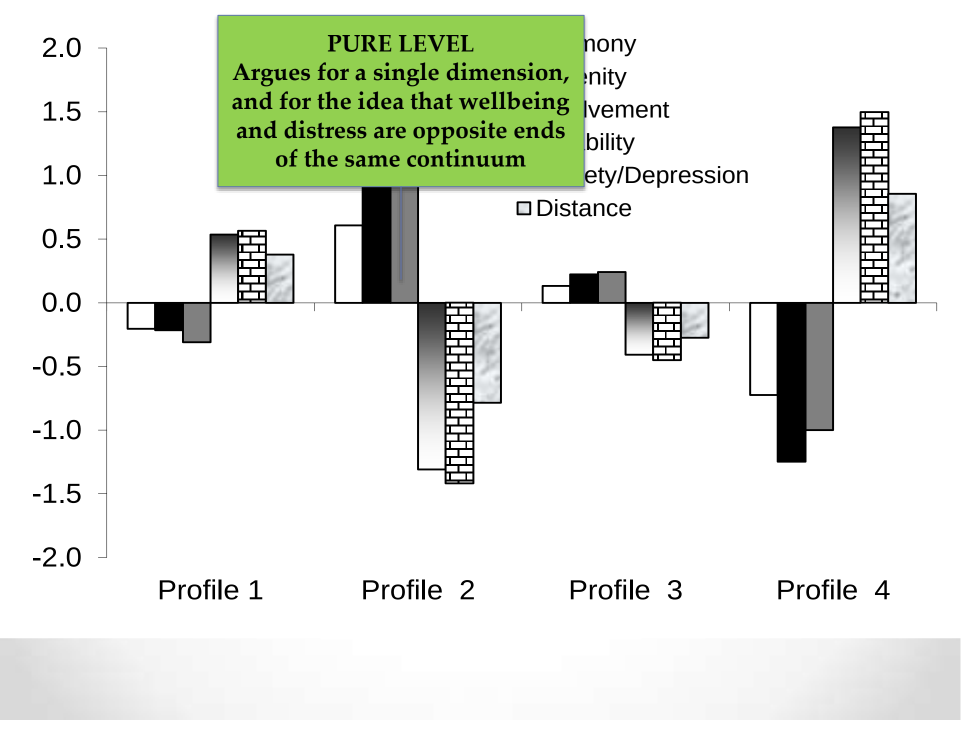
The World Health Organization (2014) defines psychological health as a state characterized not only by the absence of psychological distress, but also by the presence of psychological wellbeing.

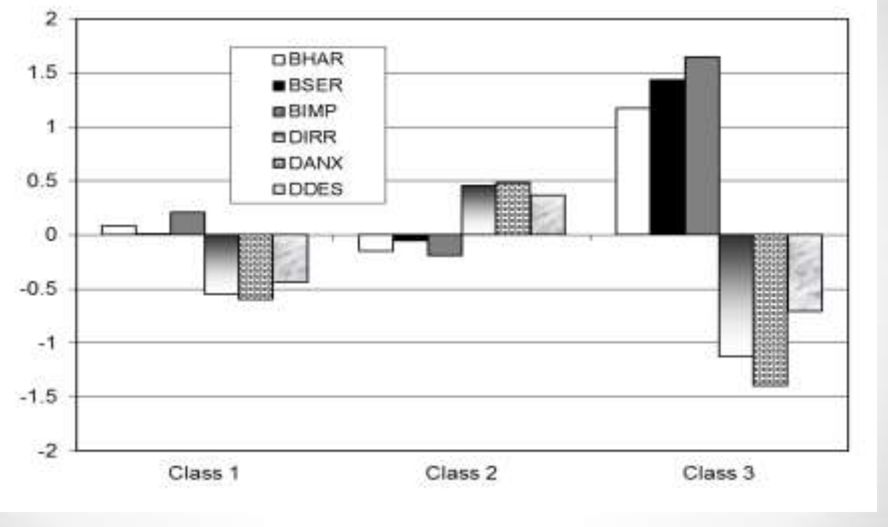


Latent Profile Model

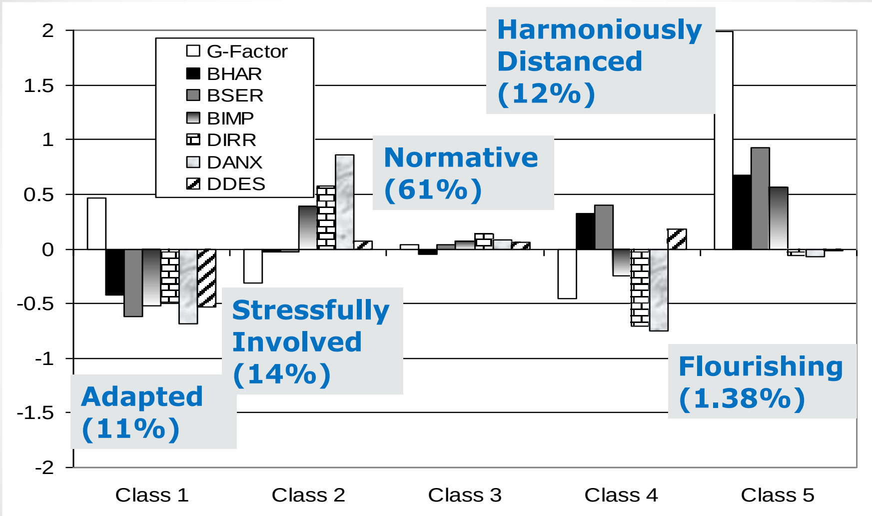




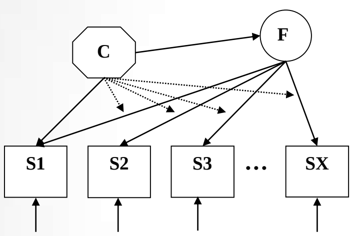
Factor Mixture Model

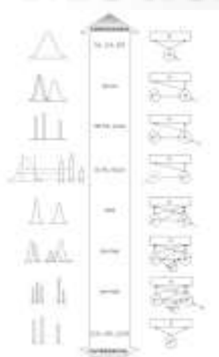


Latent Profile Model (Bifactor)



Factor Mixture Models

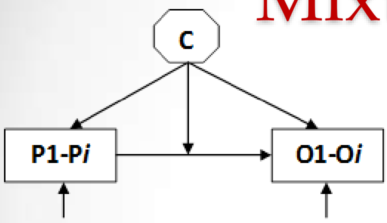




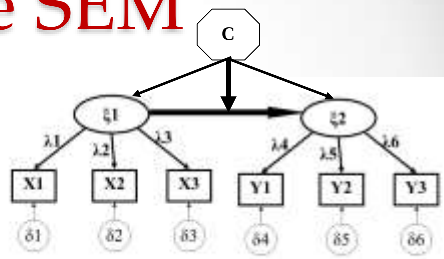
Can be used as a multiple-group CFA model to test for the invariance of a measure across unobserved subgroups of participants

Can be used as an overarching framework to explore the "true" underlying nature of psychological constructs as continuous, ordinal, nominal, etc.

Mixture Regression / Mixture SEM



Model 4: Mixture Regression Analysis



Mixture regression analysis (MRA) identifies profiles of participants differing from one another at the level of estimated relations (regressions) between constructs.

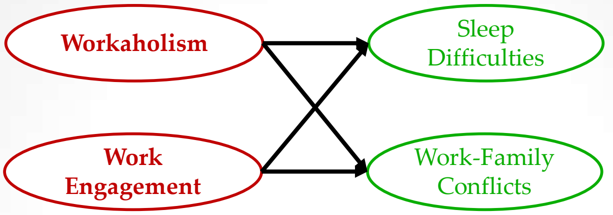
$$\boldsymbol{Y} = \boldsymbol{a_{yx}} + \boldsymbol{b_{yx}} * \boldsymbol{X} + \boldsymbol{\delta}$$

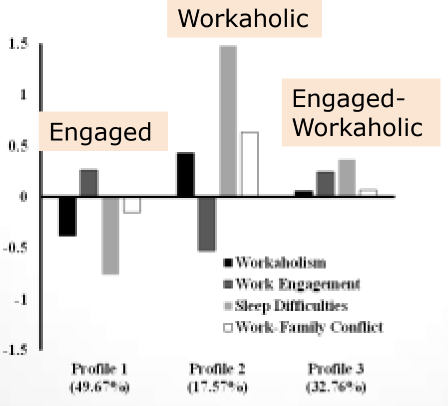
?

Chénard-Poirier, L.-A., Morin, A.J.S., & Boudrias, J.-S. (In Press). On the merits of coherent leadership empowerment behaviors: A mixture regression approach. *Journal of Vocational Behavior*.

Gillet, N., Morin, A.J.S., Sandrin, E., & Houle, S.A.

Upcoming !





	Profile 1	Profile 2	Profile 3
Engagement –> Work-Family Conflicts	.041 (.086)	.004 (.241)	-.015 (.171)
Engagement –> Sleeping Difficulties	.023 (.095)	.155 (.154)	.417 (.316)
Workaholism –> Work-Family Conflicts	.550 (.059)**	.440 (.153)*	.582 (.097)**
Workaholism –> Sleeping Difficulties	.244 (.121)*	.287 (.171)	-.293 (.257)

Construct Validation

Construct validation is the only way to demonstrate the meaningfulness of latent profile solutions

- Heuristic Value
- Theoretical Conformity and Value
- Statistical adequacy

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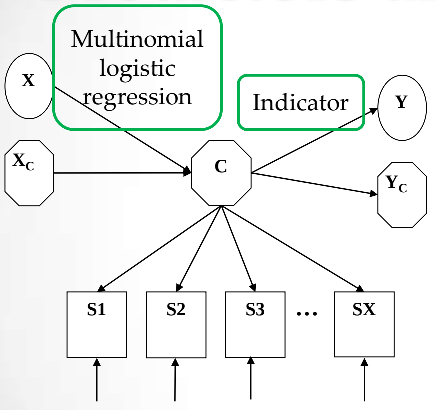
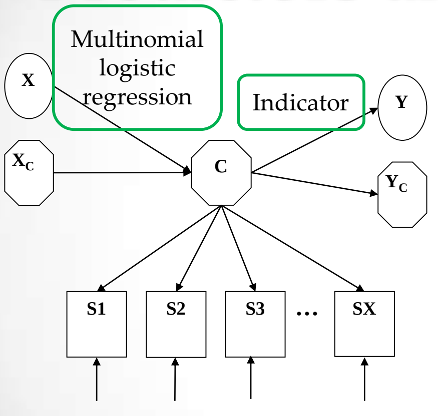
- **Shows meaningful and well-differentiated relations to key covariates:**
  - **Predictors**
  - **Correlates**
  - **Outcomes.**

Predictors and Outcomes



This is a key advantage of mixture models, relative to cluster analyses.

Predictors and Outcomes

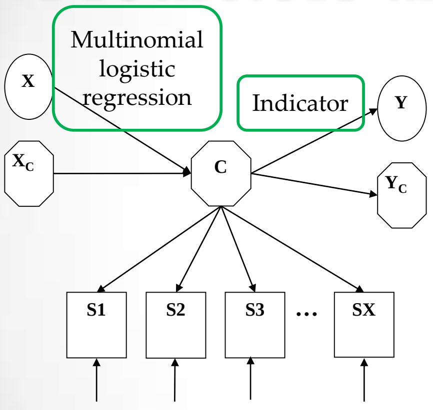


But these should not change the nature of the profiles.

Always conduct the class enumeration process before adding covariates (Diallo et al., 2016).

Solution 1. Use the start values from the retained solution and turn off the random start function

Predictors and Outcomes



But these should not change the nature of the profiles.

Solution 2: Auxiliary functions:
(E) For simple correlates
(DCON) (DCAT) for outcomes
(R3STEP) for predictors
(DU3STEP) (DE3STEP) for continuous outcomes
(BCH) for continuous outcomes

Construct Validation

Construct validation is the only way to demonstrate the meaningfulness of latent profile solutions

- Heuristic Value
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- Statistical adequacy
- Shows meaningful and well-differentiated relations to key covariates: Predictors – Correlates – Outcomes.
- **Generalizes across samples and time points.**

Construct Validation

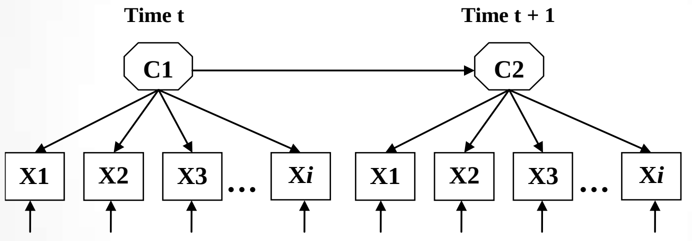
Construct validation is the only way to demonstrate the meaningfulness of latent profile solutions

- Heuristic Value
- Theoretical Conformity and Value
- Statistical adequacy
- Shows meaningful and well-differentiated relations to key covariates: Predictors – Correlates – Outcomes.
- **Generalizes across samples and time points.**

Testing the Generalizability of LPA Solutions:

Morin, A.J.S., Meyer, J.P., Creusier, J., & Biétry, F. (2016). Multiple-group analysis of similarity in latent profile solutions. *Organizational Research Methods*, *19*, 231-254.

Latent Transition Analysis



Kam, C., Morin, A.J.S., Meyer, J.P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management*, *42* (6), 1462-1490.

For applications, see:

Morin, A.J.S., & Litalien, D. (2017). Webnote: Longitudinal Tests of Profile Similarity and Latent Transition Analyses. Montreal, QC: Substantive Methodological Synergy Research Laboratory.

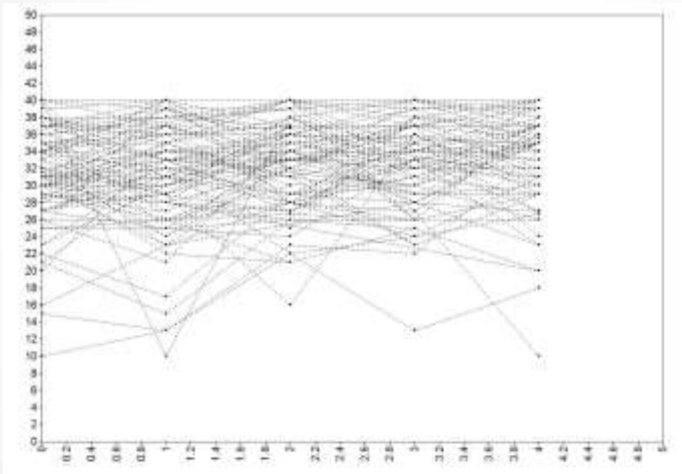
http://smslabstats.weebly.com/uploads/1/0/0/6/100647486/lta_distributional_similarity_v02.pdf

Latent Transition Analysis

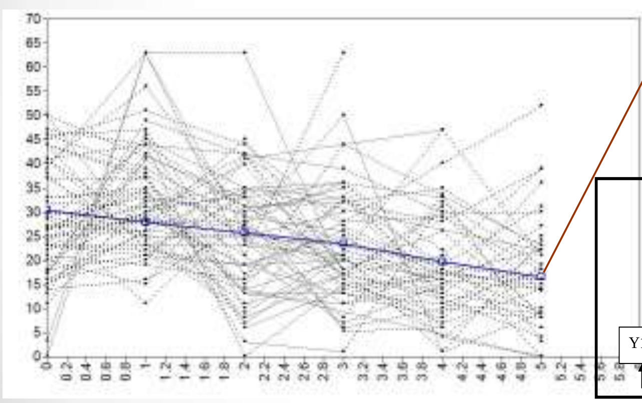
- Latent transition analyses (LTA) are a very broad class of models that can be used to assess the connections between any number of latent categorical variables.
- Due to modern computer limitations, these models are typically limited to 3, sometimes 4, latent categorical variables.
- These models can be used to assess the connections between any type of latent categorical variable (LPA, MRA, growth mixtures) based on the same, or different, sets of indicators assessed at different, or similar, time points.
- The typical application of LTA is longitudinal, and assess the connection between two LPA models based on the same set of indicators measured at different time points.
- LTA can thus be used to assess the similarity of LPA solutions over time.

Growth Mixture Analyses GMA/GMM

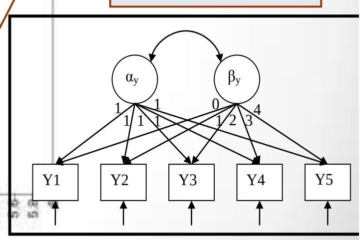
Individual trajectories



Latent curve models allow one to synthesize individual trajectories with few latent parameters through a restricted factor model.



An average trajectory with a random intercept and slope is estimated



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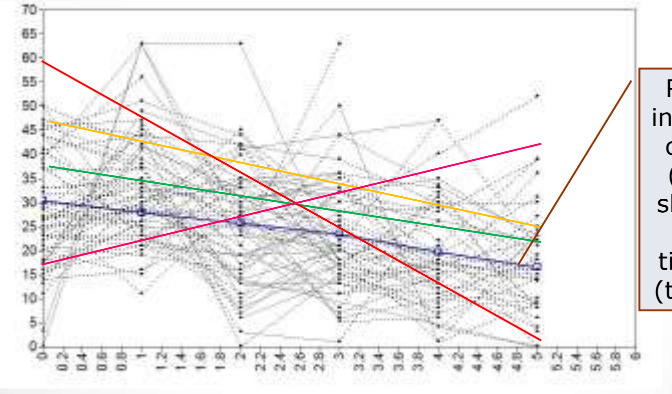
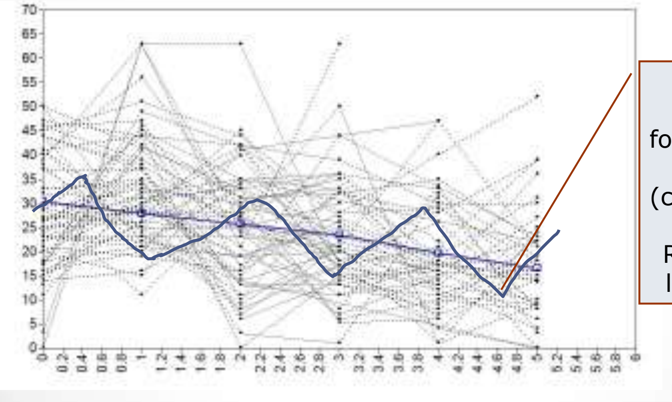


Random: Each individual has its own trajectory (intercept and slope variance). Model-based time-structured (trait) variability

Latent curve models allow one to synthesize individual trajectories with few latent parameters through a restricted factor model.



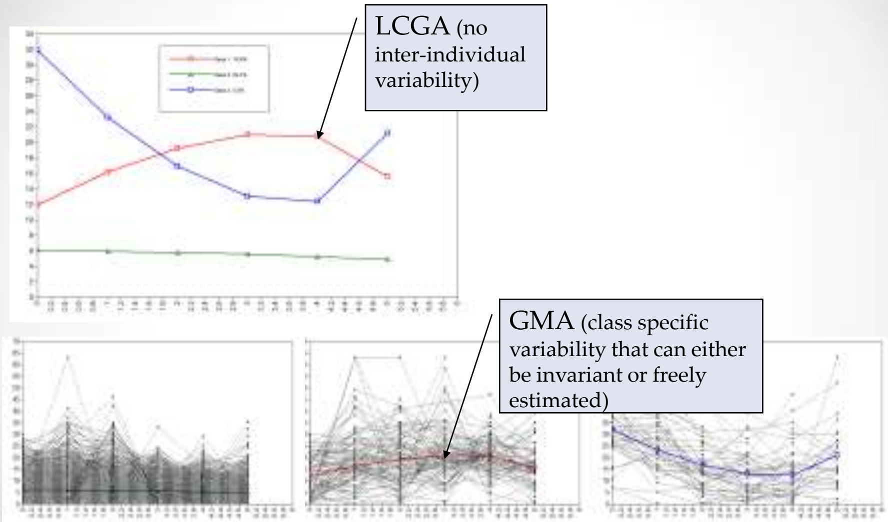
Residuals: Few persons follow a perfectly linear (curvilinear, etc.) trajectory. Residual state-like variability.

Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). Growth Mixture Modeling of adolescents trajectories of anxiety across adolescence: The impact of untested invariance assumptions on substantive interpretations. *Structural Equation Modeling*.

~ 1000 Montreal adolescents measured 5 times over a 4 year period.

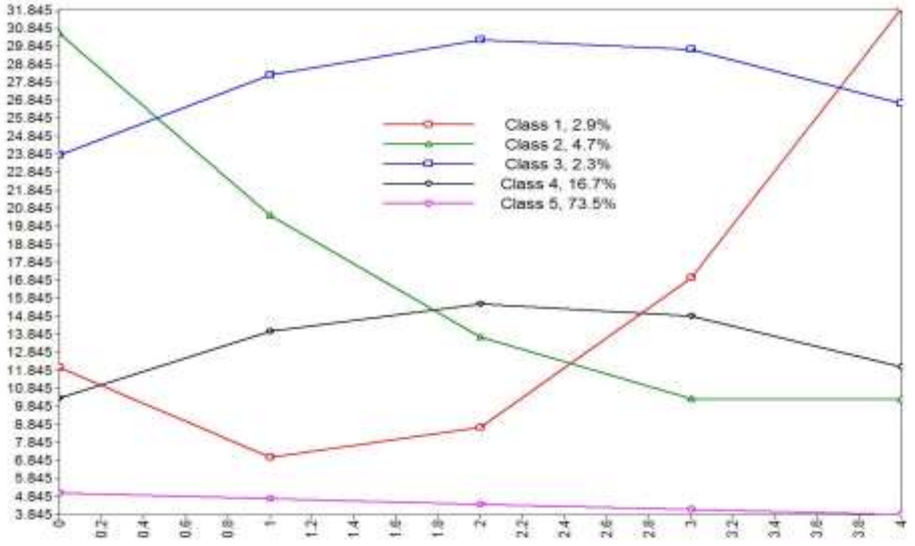
GMA Vs LCGA

LCGA (no inter-individual variability)

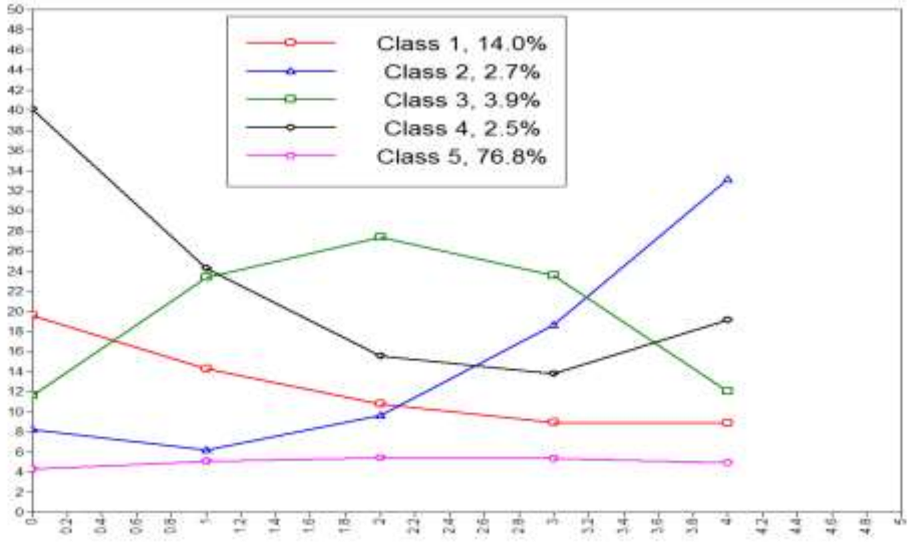


GMA (class specific variability that can either be invariant or freely estimated)

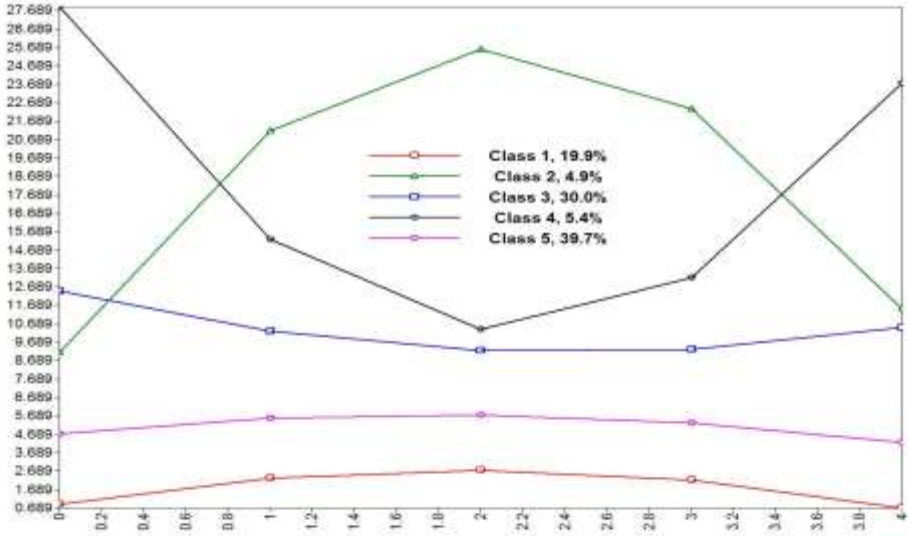
Results: LCGA



Results: GMA, Mplus default



Results: GMA, free estimation

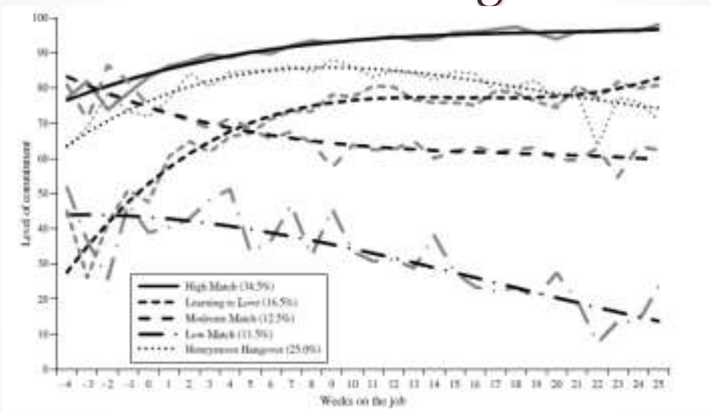


A simulation study

- Diallo, T.M.O, Morin, A.J.S. & Lu, H. (2016). Impact of misspecifications of the latent variance-covariance and residual matrices on the class enumeration accuracy of growth mixture models. *Structural Equation Modeling*, *23* (4), 507-531. DOI: 10.1080/10705511.2016.1169188
- In a series of 4 studies, we contrasted population models corresponding to the LCGA, Mplus default, or distinct latent variance-covariance matrices, while also considering presence of class-invariant or distinct residual structures.
- Overall, our results clearly show the advantages of relying on freely estimated latent variance-covariance and residual structures in each latent classes.

But this also depends on sample size and convergence

N = 72

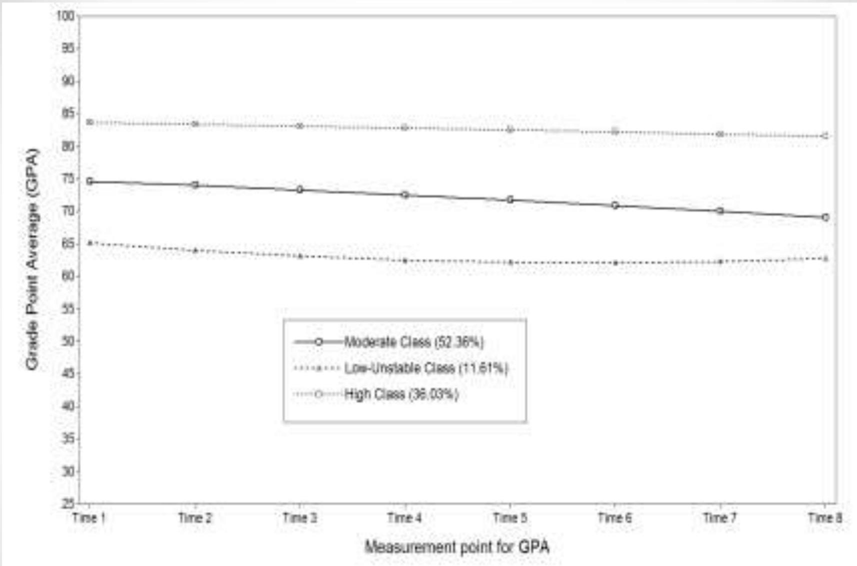


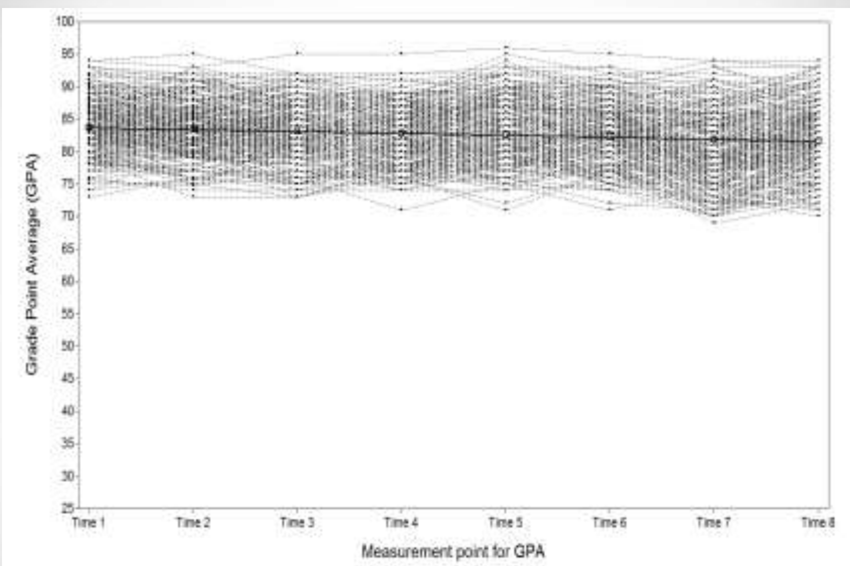
Solinger, O.N., Van Olffen, W., Roe, R.A., & Hofmans, J. (2013) On Becoming (Un)Committed: A Taxonomy and Test of Newcomer Onboarding Scenarios. *Organization Science*, *24*, 1640–1661.

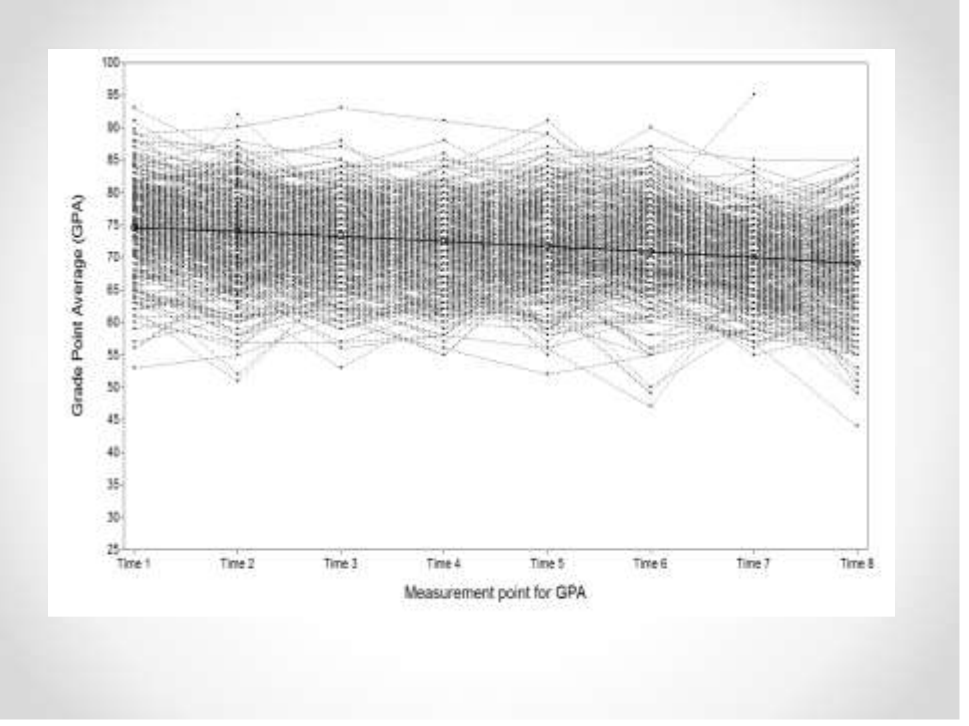
Morin, A.J.S., Rodriguez, D., Fallu, J.-S., Maïano, C., & Janosz, M. (2012). Academic Achievement and Adolescent Smoking: A General Growth Mixture Model. *Addiction*.

741 non-smoking adolescents. Official GPA ratings obtained 8 times (beginning and end of school years).

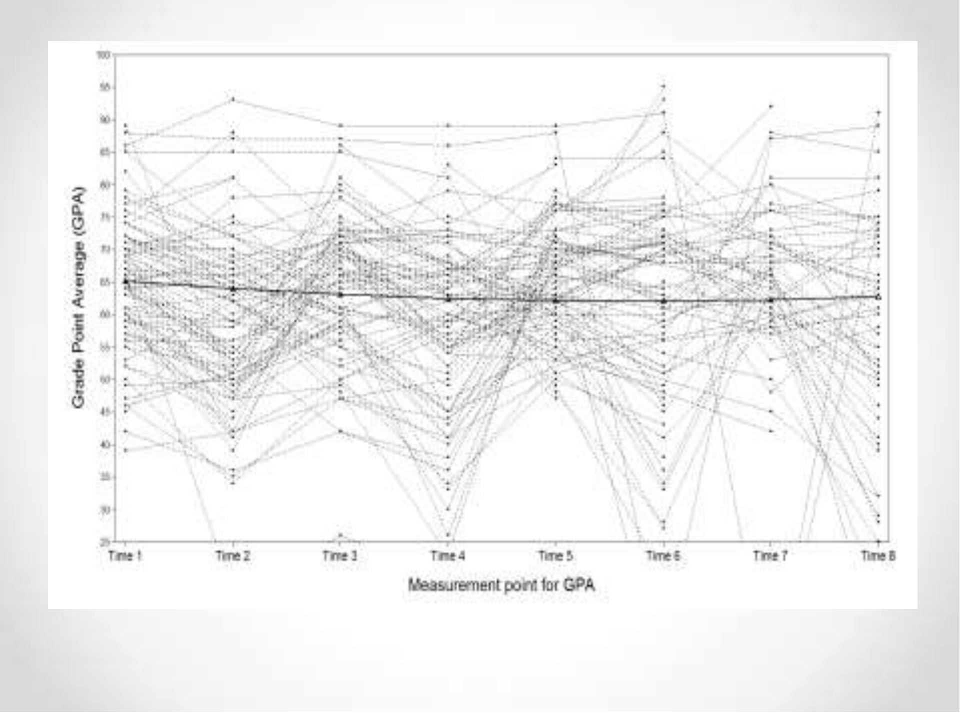
And what about ε_{yitk} ?


Grade Point Average (GPA)
Measurement point for GPA
Moderate Class (52.36%)
Low-Unstable Class (11.61%)
High Class (36.03%)

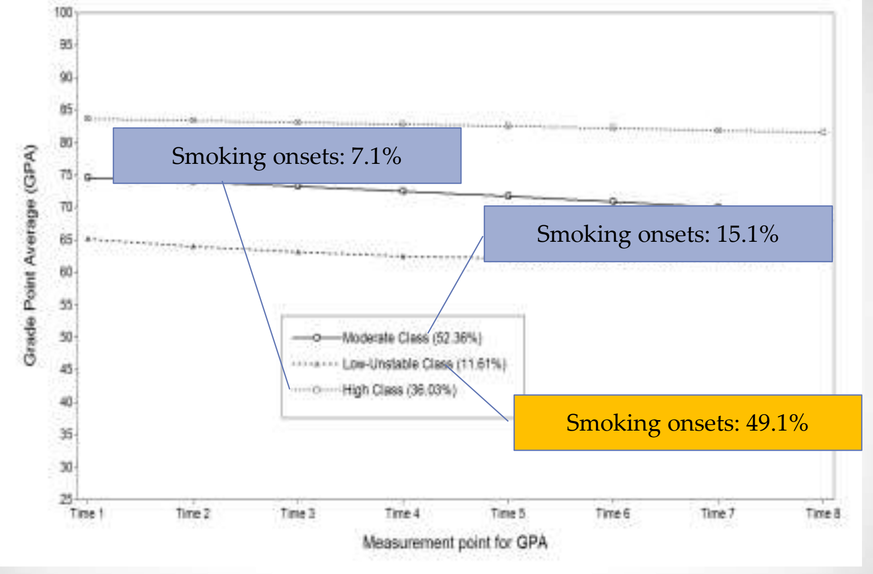

Grade Point Average (GPA)
Measurement point for GPA



Grade Point Average (GPA)
Measurement point for GPA
Time 1
Time 2
Time 3
Time 4
Time 5
Time 6
Time 7
Time 8



Grade Point Average (GPA)
Measurement point for GPA
Time 1
Time 2
Time 3
Time 4
Time 5
Time 6
Time 7
Time 8



Organizational Research Methods: Special Issue on Person-Centered Analyses

- Confirmatory LPA
- Multilevel LPA
- Extended Capabilities through Manual Auxiliary Approaches (mediation, moderation, etc.).
- K-Centres functional clustering for longitudinal data
- Among others