A PRIMER TO LATENT CLASS AND LATENT PROFILE ANAYLSIS TO CLASSIFY SUBGROUPS IN THE TBIMS NDB

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PRESENTATION

Goal of this presentation will be to:

- show the conceptual methods behind LPA/LCA and how it differs from other methods (e.g., cluster analysis)
- its advantages, e.g., incorporating individual differences and covariates within the model
- walk through how to (quickly) conduct an LPA - from importing data to results interpretation using the TBIMS-related data

WHY ME?

Research Scientist at Craig Hospital

Dually-enrolled PhD student at University of North Texas

- Experimental Psychology/Behavioral Sciences
- Educational Psychology conc. Research Measurement and Statistics

Received extensive training in latent analytic methods

BASICALLY...

Latent class or latent profile analysis is a person-centered, mixed-models approach that classifies a heterogeneous group of individuals by latent, unobserved groups based on response patterns or characteristics

Often applied to examine associations between observed variables (e.g., indicators, characteristics), assuming the existence of patterns for the purpose of classification

METHODOLOGICAL DIFFERENCES

CLUSTER ANALYSIS

Bottom-up approach

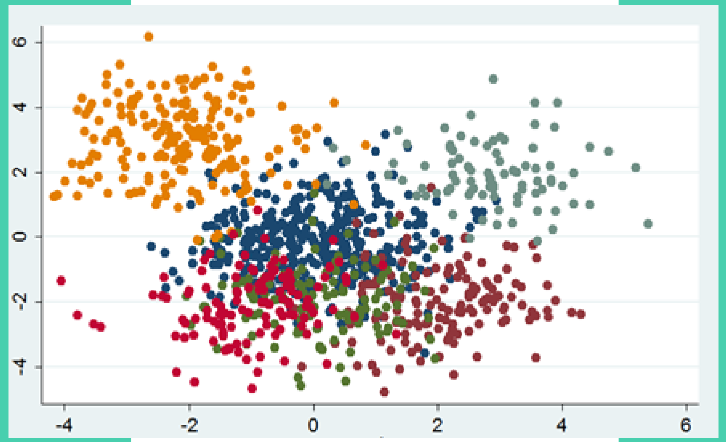
More exploratory -> data-based

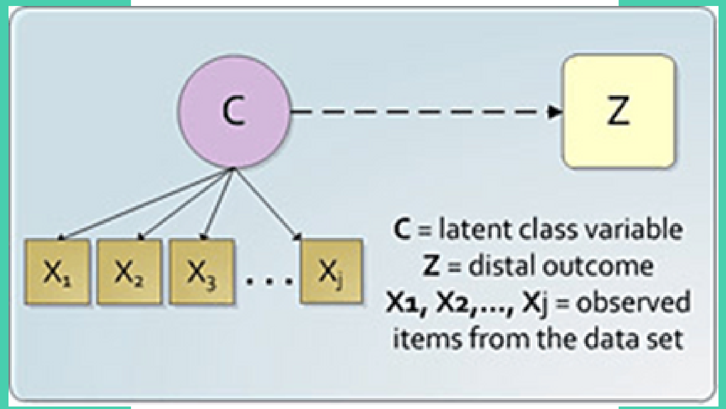
Similarities-based clustering which plots features using algorithms

- *nearest neighbors / distance*
- *density*
- *heirarchy*

"What are the closest units using distance?"

2-step: K-Means to Heirarchical Cluster





LCA/LPA

Top-down approach

"Model-based clustering" -> derives clusters using a probabilistic model to describe distribution of data

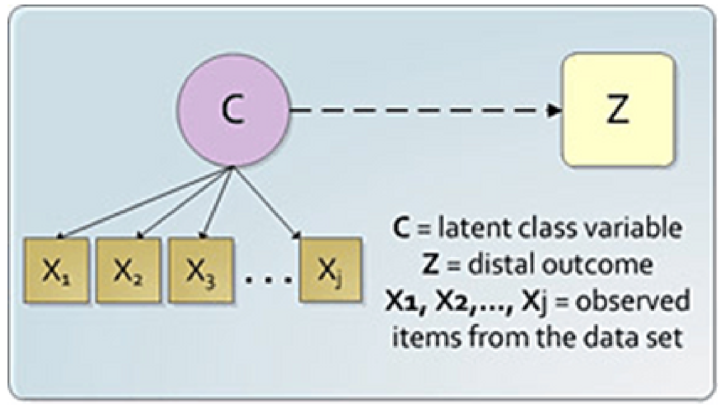
- *utilizes covariance matrix as data unit*
- *goodness of fit statistics for how well model fits the data*
- *assumptions of normality and local independence*

*Assumes latent structure**

"What are the most similar patterns based off probability?"

Class (categorical) vs. profile (continuous)

LPA/LCA is far more flexible



id	cprob1	cprob2	cprob3	cprob4	class
1	0	0	0.988	0.012	3
2	0.031	0	0.969	0	3
3	0	0	1	0	3
4	0	1	0	0	2
5	0.046	0.938	0.016	0	2
6	0	0	0.999	0.001	3
7	0	0	0.972	0.028	3
8	0	1	0	0	2
9	0	0.011	0.054	0.934	4
10	1	0	0	0	1

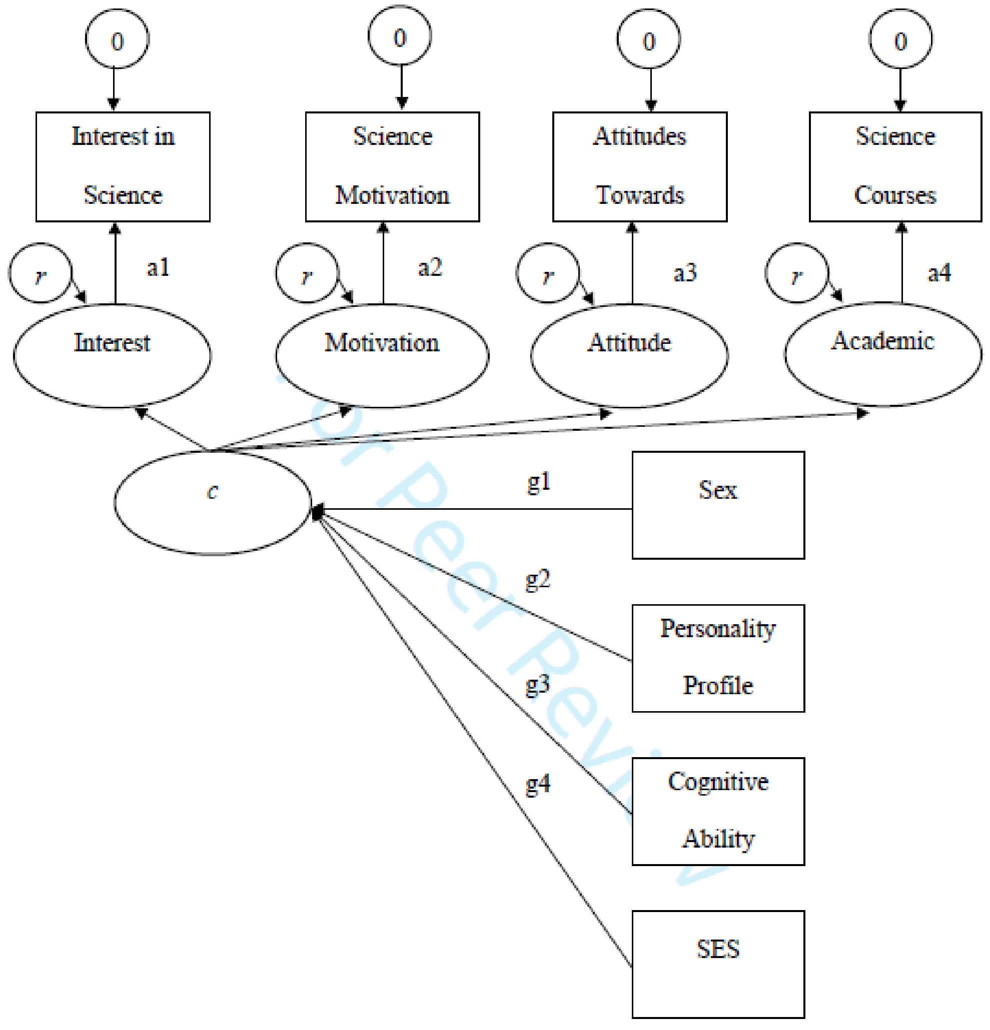


Figure 1. Example of LPA model with covariates
Ferguson, et al. (2020). International Journal of Behavioral Development.

LCA/LPA

...estimates probabilities for every individual and can be kept in model

...provides evaluation of model fit to data

...can iteratively test alternative models

... can include covariates to predict individuals' latent class membership

.... full model can be combined with other techniques (e.g., IRT, CFA, within-cluster regression in latent-class regression)

SUMMARY OF STEPS

1. Is LCA/LPA appropriate?
2. Generate hypotheses models based on theory
3. Data setup
4. Estimate models
5. Evaluate models
6. Interpret optimal model

PRACTICAL WALKTHROUGH:

REFER TO THE HANDOUT

WHY USE IT?

Traumatic brain injury (TBI) is a complex condition where heterogeneity impedes the advancement of care. Understanding the diverse presentations of TBI is crucial for personalized medicine. Our study aimed to identify clinically relevant patient endotypes in TBI using latent class analysis based on comorbidity data. We used the Medical Information Mart for Intensive Care III database

Qiu et al. 2024

To characterize latent classes of diagnostic and/or treatment procedures among hospitalized U.S. adults, 18–64 years, with primary diagnosis of TBI from 2004–2014 Nationwide Inpatient Samples, latent class analysis (LCA) was applied to 10 procedure groups and differences between latent classes on injury, patient, hospital and healthcare utilization outcome characteristics were modeled using multivariable regression.

Beydoun et al. 2020

Introduction: Post-traumatic stress symptoms (PTSS) are known to contribute to postconcussion symptoms and functional status following mild traumatic brain injury (mTBI). Identifying symptom cluster profiles provide an opportunity to better understand PTSS and their influence on these outcomes. In this study, latent profiles of PTSS following mTBI were identified, and their association with mTBI outcomes was examined. The predictive role of demographic and injury related variables on profile membership was also explored.

Faulkner et al. 2023

IMPORTANCE Heterogeneity across patients with traumatic brain injury (TBI) presents challenges for clinical care and intervention design. Identifying distinct clinical phenotypes of TBI soon after injury may inform patient selection for precision medicine clinical trials.

OBJECTIVE To investigate whether distinct neurobehavioral phenotypes can be identified 2 weeks after TBI and to characterize the degree to which early neurobehavioral phenotypes are associated with 6-month outcomes.

Brett et al., 2021

Objective:

To examine the intersectional impact of multiple social identities vulnerable to systemic disadvantage following TBI on mortality, opioid usage during acute hospitalization, and discharge location.

Starosta et al., 2023

Latent Class Analysis to Classify Injury Severity in Pediatric Traumatic Brain Injury Keenan et al., 2020.

The present study uses LCA to distinguish severity groups from 433 children 2.5-15 years of age with TBI.

Indicator variables available within 48 h post-injury were evaluated to define subgroups:

- ED GCS
- hospital motor GCS
- Abbreviated Injury Score (AIS)
- Rotterdam Score
- ED hypotension
- pre-hospital LOC
- intubation
- seizures
- sedation

Key features of latent classes

The indicator variables for each latent class are displayed in Figure 1, in which gradations of the indicators are represented from absent (no color), and least severe (light gray) to most severe (black). Latent class probabilities and item response probabilities are shown in Table 2. External validation of the classes was provided by evaluating whether groups differed with respect to the severity of other clinical indicators not included in the LCA. As seen in Table 3, although the demographic features of the cohort were similar across classes, injury characteristics differed substantively.

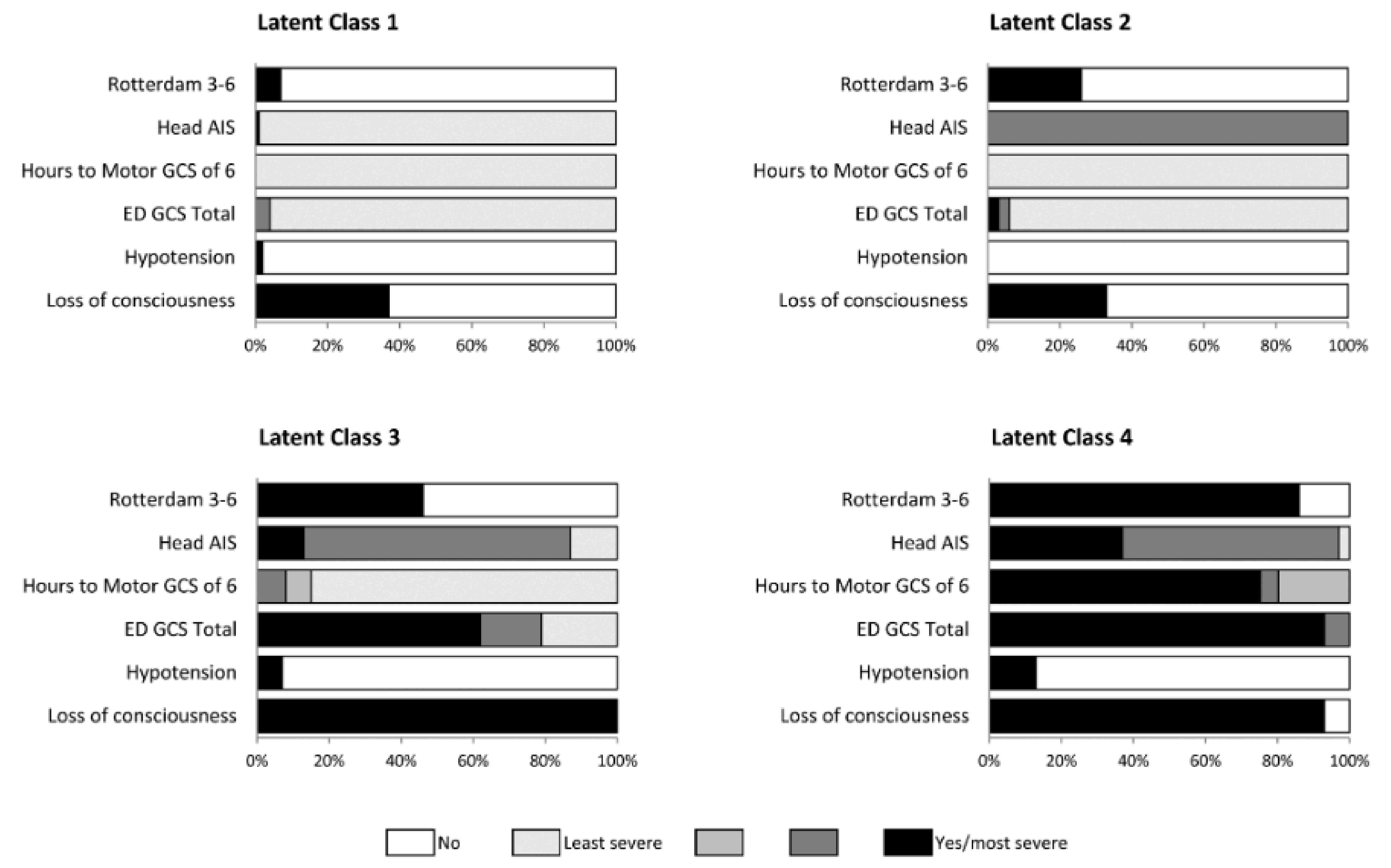


FIG. 1. Indicator variables in each latent class.

Latent Class Analysis to Classify Injury Severity in Pediatric Traumatic Brain Injury Keenan et al., 2020.

The present study uses LCA to distinguish severity groups from 433 children 2.5–15 years of age with TBI.

Outcomes were examined by GCS (primary) and AIS (secondary) classification alone to assess whether LCA provided improved outcome prediction

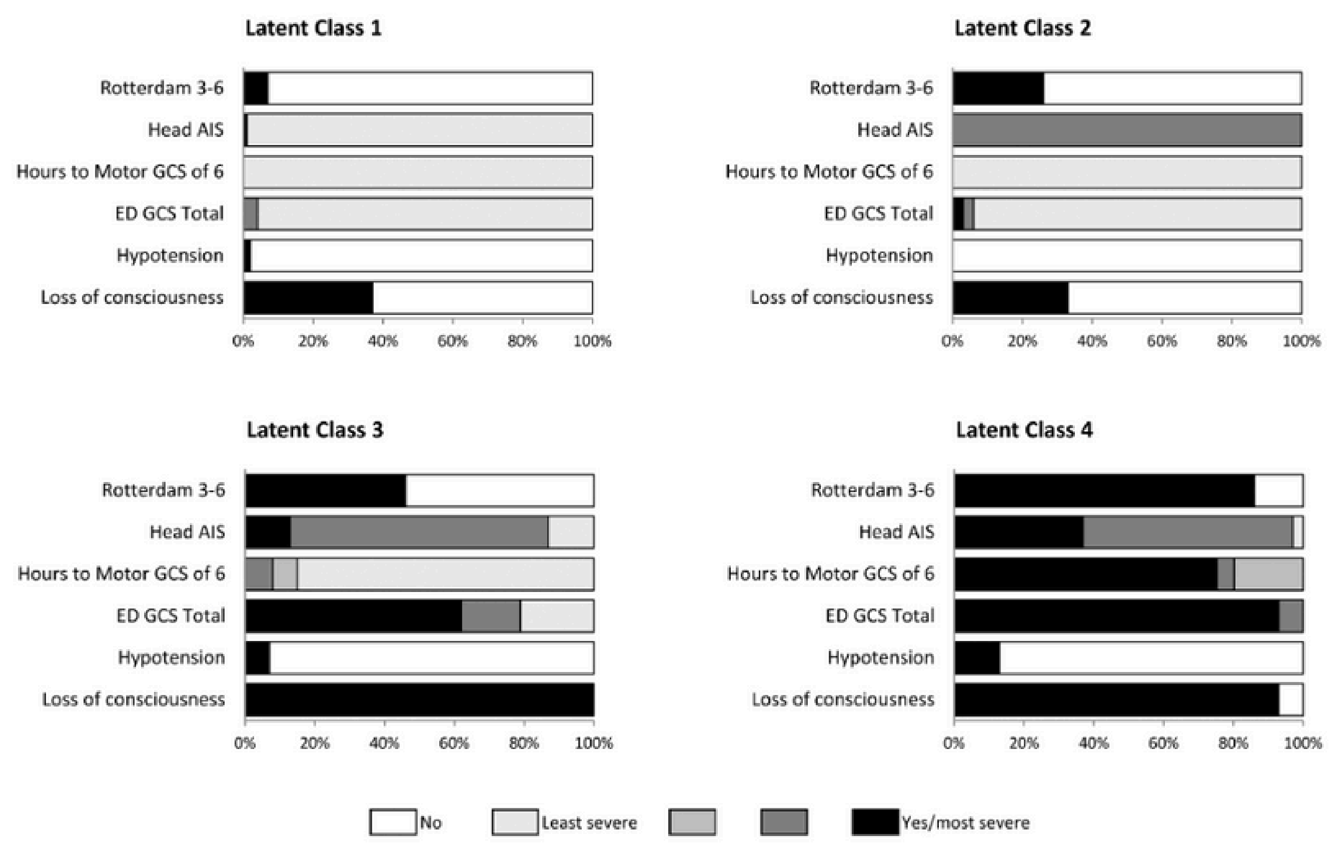


FIG. 1. Indicator variables in each latent class.

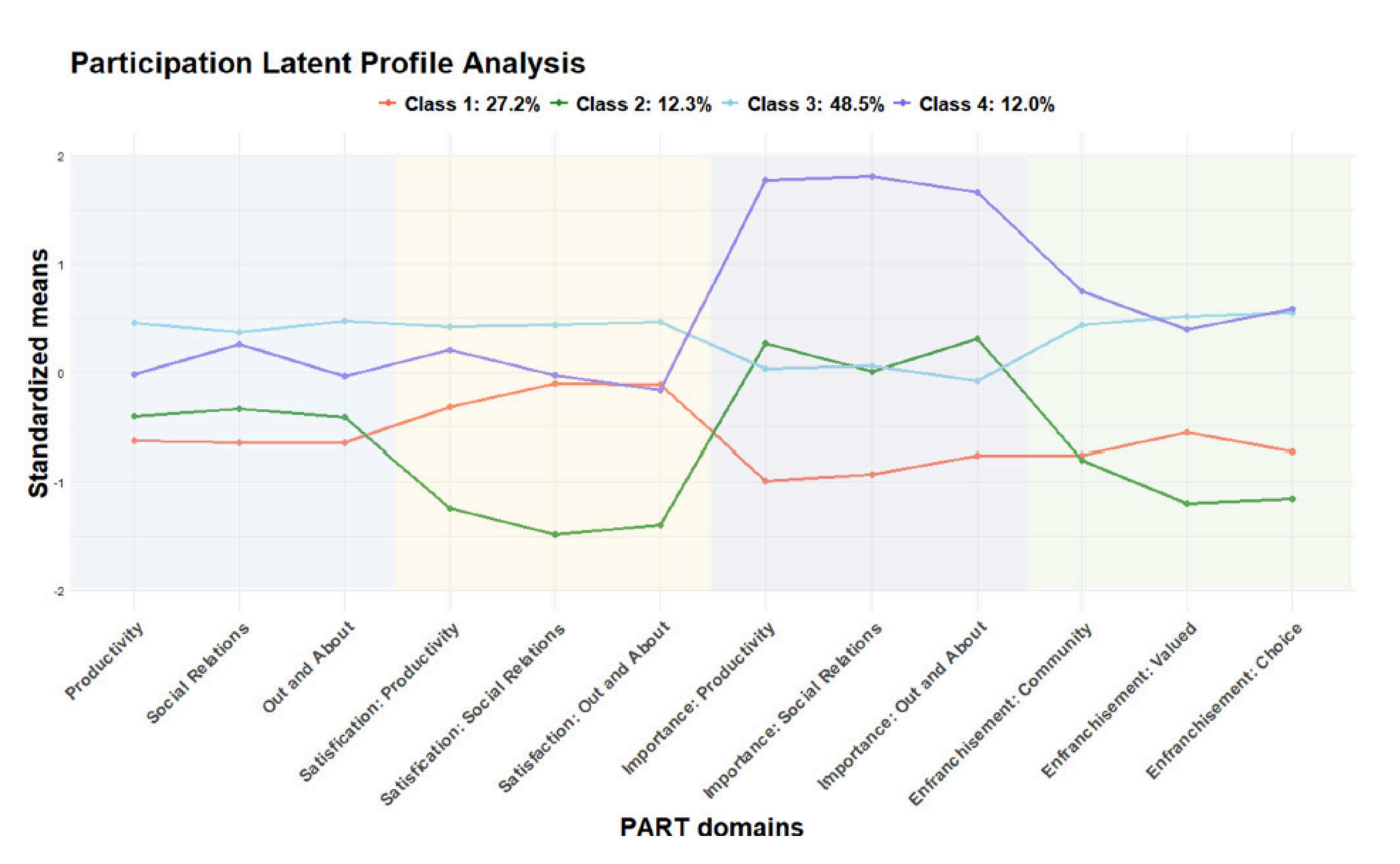
Table 4. Latent Class Assignment by Original GCS-Defined TBI Severity

	Latent class (LC)			
	LC 1	LC 2	LC 3	LC 4
Original severity classification	(*n* = 150)	(*n* = 162)	(*n* = 75)	(*n* = 46)
Mild (*n* = 161)	76.4%	22.4%	1.2%	0.0%
Complicated mild (*n* = 144)	13.9%	83.3%	2.8%	0.0%
Moderate (*n* = 29)	24.1%	10.3%	55.2%	10.3%
Severe (*n* = 99)	0.0%	3.0%	53.5%	43.4%

GCS, Glasgow Coma Scale; TBI, traumatic brain injury.

Developing multidimensional participation profiles after traumatic brain injury: a TBI model systems study
Juengst et al., 2024

To characterize societal participation profiles in N = 408 individuals after moderate-severe traumatic brain injury (TBI) objective (**Frequency**) and subjective (**Satisfaction, Importance, Enfranchisement**) dimensions.



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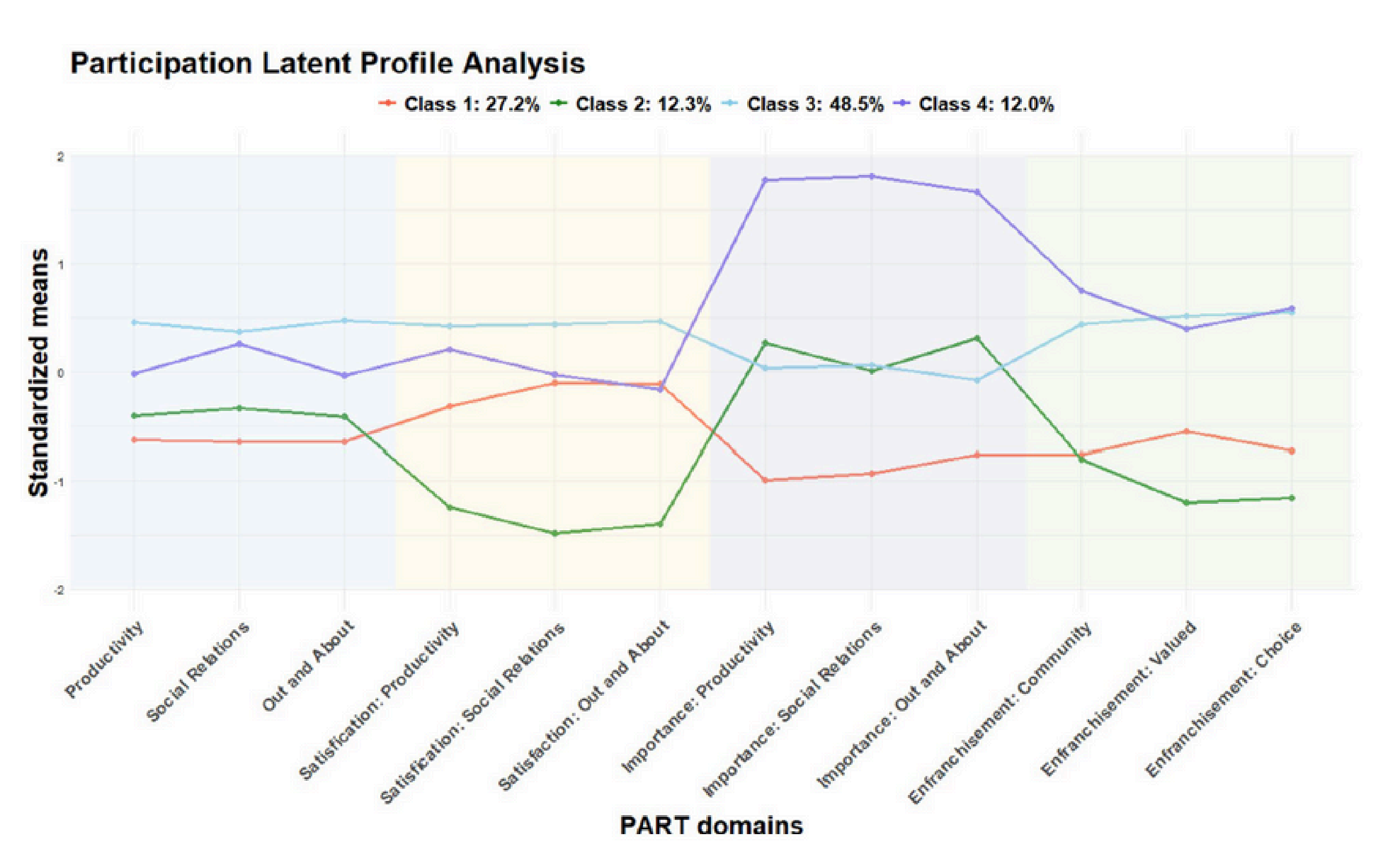

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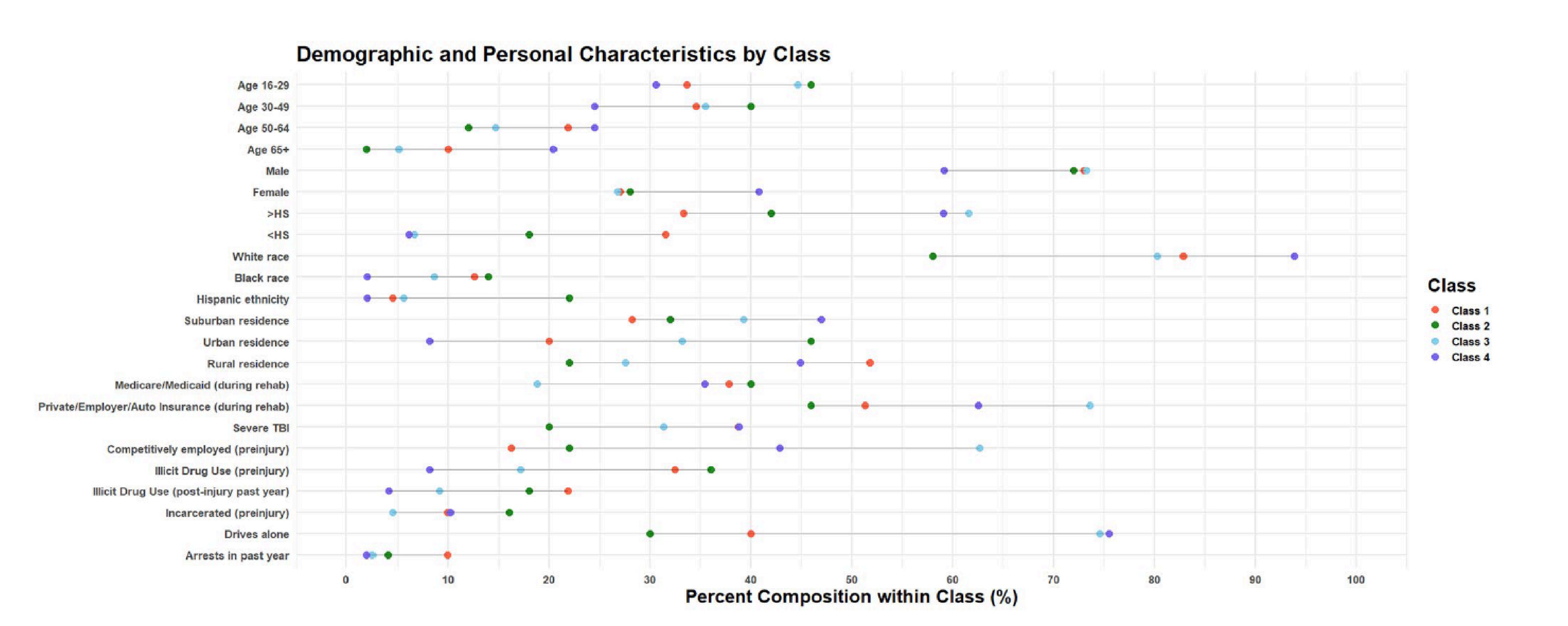
Dot plot of personal characteristics by profile group. Percentages represent the percent composition of a variable within a given profile group.



PRACTICAL EXAMPLE:
JUENGST ET AL. 2024

SUMMARY OF STEPS

1 Is LCA/LPA appropriate?

N > 300 sample

Cross-sectional data

Hidden subgroups, need for more meaningful clinical syndromes, heterogeneity in your sample?

2 Generate hypotheses models based on theory

Selection of indicators based on RQ

Exclude overlapping indicators

Exclude outcome data as indicators

3 Data setup

Transformation of extreme scales (e.g., z-scores)

Uniform scale (unidirectional)

Consider collapsing categories <10% of sample

Non-parametric data may need to be transformed

Test correlations of indicators for collinearity

FIML/imputation for missing data

4 Estimate models

Will likely estimate multiple models (iterative process)

Generate fit statistics

5 Evaluate models

Comparison of model performance based on goodness of fit statistics, entropy, significance tests, class sizes, class probabilities, theoretical sense, parsimony

6 Interpret optimal model

Interpretation of classes based on indicators relative to each other and/or general sample

Use outcome measures or other key variables to demonstrate classes are of discriminatory value

LAST CONSIDERATIONS

Garbage in, garbage out

Are classes telling you anything unique or above and beyond current or single classification systems? (i.e., know when to quit)

What will you do with these subtypes?

EXAMPLES

- Brett, B. L., Kramer, M. D., Whyte, J., McCrea, M. A., Stein, M. B., Giacino, J. T., ... & TRACK-TBI Investigators. (2021). Latent profile analysis of neuropsychiatric symptoms and cognitive function of adults 2 weeks after traumatic brain injury: findings from the TRACK-TBI study. JAMA Network Open, 4(3), e213467-e213467.
- Faulkner, J. W., Snell, D. L., Theadom, A., de Terte, I., & Low, R. (2023). Patterns of post-traumatic stress symptoms in mild traumatic brain injury and their relationship with outcomes: a latent profile analysis. Journal of Clinical and Experimental Neuropsychology, 45(3), 230-241.
- Juengst, S. B., Agtarap, S., Venkatesan, U. M., Erler, K. S., Evans, E., Sander, A. M., ... & Whiteneck, G. G. (2024). Developing multidimensional participation profiles after traumatic brain injury: a TBI model systems study. Disability and Rehabilitation, 46(11), 2385-2395.
- Juengst, S. B., Kumar, R. G., Venkatesan, U. M., O'Neil-Pirozzi, T. M., Evans, E., Sander, A. M., ... & Whiteneck, G. G. (2024). Predictors of multidimensional profiles of participation after traumatic brain injury: a TBI model systems study. The Journal of Head Trauma Rehabilitation, 10-1097.
- Keenan, H. T., Clark, A. E., Holubkov, R., Cox, C. S., Patel, R. P., Moore, K. R., & Ewing-Cobbs, L. (2020). Latent class analysis to classify injury severity in pediatric traumatic brain injury. Journal of Neurotrauma, 37(13), 1512-1520.
- Qiu, H., Zador, Z., Lannon, M., Farrokhyar, F., Duda, T., & Sharma, S. (2024). Identification of clinically relevant patient endotypes in traumatic brain injury using latent class analysis. Scientific Reports, 14(1), 1294.
- Starosta, A. J., Mata-Greve, F., Humbert, A., Zheng, Z., Prado, M. G., Au, M. A., ... & Hoffman, J. M. (2023). Intersectionality of systemic disadvantage on mortality and care following TBI. The Journal of Head Trauma Rehabilitation, 38(2), 137-146.

REFERENCES

- Ferguson, S. L., G. Moore, E. W., & Hull, D. M. (2020). Finding latent groups in observed data: A primer on latent profile analysis in Mplus for applied researchers. International Journal of Behavioral Development, 44(5), 458-468.
- Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. Translational Issues in Psychological Science, 4(4), 440.
- Oberski, D. (2016). Mixture models: Latent profile and latent class analysis. Modern Statistical Methods for HCI, 275-287.
- Sinha, P., Calfee, C. S., & Delucchi, K. L. (2021). Practitioner's guide to latent class analysis: methodological considerations and common pitfalls. Critical Care Medicine, 49(1), e63-e79.
- Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. Journal of Vocational Behavior, 120, 103445.
- Tein, J. Y., Coxe, S., & Cham, H. (2013). Statistical power to detect the correct number of classes in latent profile analysis. Structural Equation Modeling: A Multidisciplinary Journal, 20(4), 640-657.