Unrau, Joshua[1], Percie du Sert, Olivier[1], Raucher-Chéné, Delphine[1], Joober, Ridha[1], Malla, Ashok[1], Lepage, Martin[1]
[1] Douglas Mental Health University Institute, McGill University, Montreal, Canada

Identifying Distinct Trajectories of Negative Symptoms Following First-Episode Psychosis: A Two-Year Study of Patients Admitted to an Early Intervention Service

BACKGROUND

➔ Negative symptoms associated with psychotic disorders include blunted affect, alogia (poverty of speech), avolition, asociality, and anhedonia (inability to feel pleasure)

➔ The course of negative symptoms following first-episode psychosis (FEP) is markedly heterogeneous, with negative symptom remission a key predictor of functional outcomes[1]

➔ While many have theorized that negative symptoms could resolve into more homogeneous clusters[2], few studies have applied a **data-driven approach to characterize negative symptom trajectories**

We aimed to identify **distinct trajectories of negative symptoms** within an FEP cohort undergoing two years of treatment in an early intervention service.

After identifying the most parsimonious model, we explored **predictors of latent class membership** using multinomial logistic regression.

METHODS

Participants and Treatment Setting

➔ 326 patients admitted to the Prevention and Early Intervention Program for Psychosis (2003 - 2018)

➔ Inclusion Criteria: Aged 14-35, affective or non-affective psychosis, minimum of 5 assessments, IQ at least 70, less than one month of any type of treatment prior to baseline assessment

➔ During the study period, patients were supported with a variety of specialized, phase-specific interventions such as medication management, family support, cognitive-behavioral therapy, and work preparation programs[3]

Data Collection

➔ Assessments via semi-structured interview at nine time points (baseline, months 1, 2, 3, 6, 9, 12, 18, 24)

➔ Demographic factors and IQ recorded at baseline

➔ Scale for the Assessment of Negative Symptoms (SANS) global scores calculated excluding global rating of attention

➔ Patients given retrospective diagnosis 1 year after admission

Analysis

1. Determine Optimal Latent Growth Model

➔ Using Mplus Version 8.4, we performed Latent Class Growth Analysis to identify clusters of patients with similar longitudinal trajectories of SANS global scores.

➔ We used the MplusAutomation package for R to systematically test class structure, polynomial order, and model restrictions, following model selection procedures outlined in a recent paper[4].

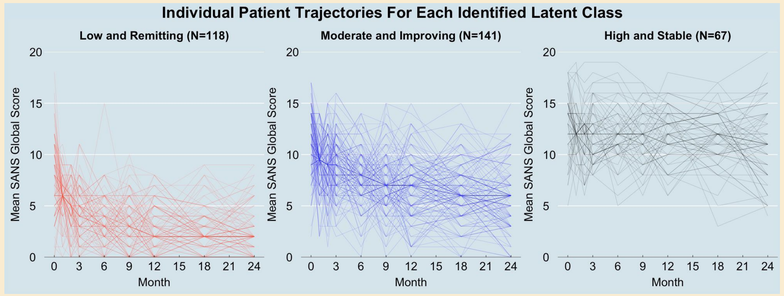
2. Identify Predictors of Class Membership

➔ After identifying the most parsimonious model, we used mixed modeling and chi-square tests to identify potentially significant predictors of latent class membership.

➔ We then performed univariate multinomial logistic regressions for all significant results, using the least pernicious trajectory as the reference group.

RESULTS

Three Negative Symptom Trajectory Classes



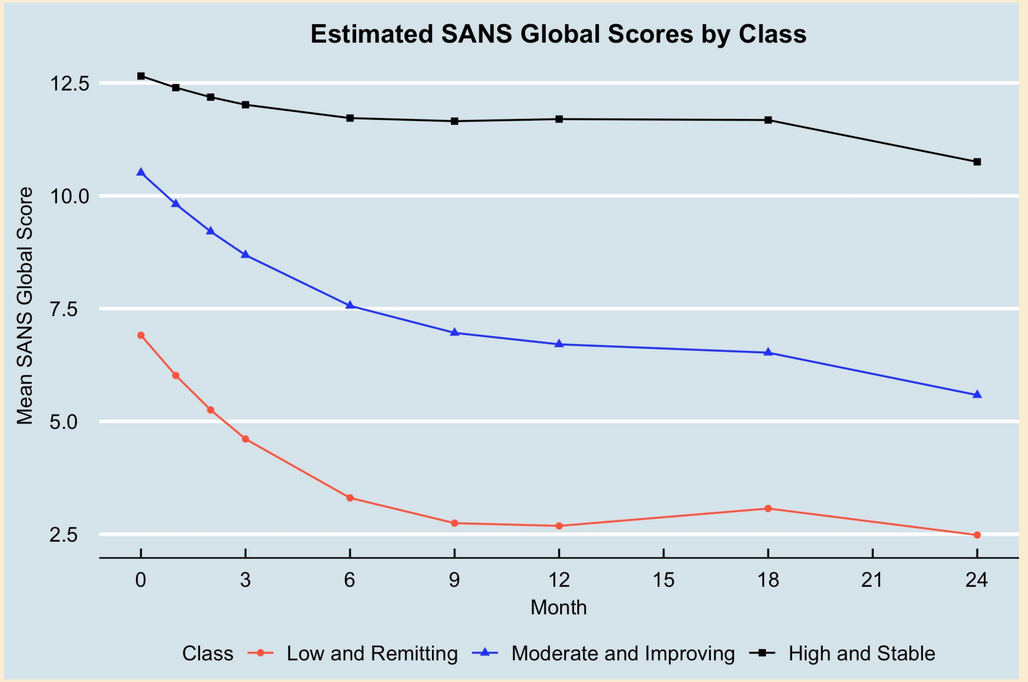
Predictors of High and Stable and Moderate and Improving Trajectories: Younger Age, Non-Affective Diagnosis, Lower IQ, Higher SAPS Global Score, Fewer Years of Education

Sample Characteristics

	Sample (N = 326)
Age at Entry	23.71 ± 4.78
DUP (Weeks)	43.18 ± 88.28
Non-Affective	214 (65.64%)
IQ	98.45 ± 14.80
Male Sex	215 (65.95%)
SAPS at Baseline	11.81 ± 3.08
Years of Education	11.93 ± 2.66

Odds Ratios for Multinomial Logistic Regressions

	High and Stable		Moderate and Improving	
	Odds Ratio (95% CI)	P-Value	Odds Ratio (95% CI)	P-Value
Age at Entry	**0.875 (0.830-0.923)**	**<.001**	**0.918 (0.878-0.960)**	**0.001**
DUP (Weeks)	1.005 (0.999-1.012)	0.140	1.005 (0.999-1.012)	0.198
Non-Affective	**3.660 (2.049-6.534)**	**0.039**	**2.441 (1.585-3.758)**	**0.024**
IQ	**0.960 (0.941-0.980)**	**0.001**	**0.977 (0.962-0.993)**	**0.016**
Male Sex	2.689 (1.535-4.712)	0.065	2.058 (1.338-3.166)	0.050
SAPS at Baseline	**1.138 (1.041-1.244)**	**0.025**	**1.100 (1.028-1.176)**	**0.028**
Years of Education	**0.781 (0.700-0.871)**	**<.001**	**0.830 (0.765-0.901)**	**<.001**



DISCUSSION

➔ Our findings provide converging evidence from a data-driven approach for the existence of subgroups of FEP patients

➔ While we were able to identify distinct trajectories of negative symptoms, it is important to note that there remains considerable variance within each latent class.

➔Future research should explore the extent to which latent classes converge with existing constructs such as persistent negative symptoms and deficit syndrome

➔ Given the ever-growing adoption of big data techniques within the scientific community, our findings also provide a theoretical foundation for future research exploring more targeted interventions within subgroups of FEP patients

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Contact
joshua.unrau@mail.mcgill.ca

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