

Growth mixture modeling of stimulant use treatment effects and differential trajectories: Evidence from two contingency management clinical trials

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BACKGROUND AND AIM

- Growth mixture modeling (GMM) represents a unique and rigorous statistical approach that could help treatment developers better understand how individuals differ in their response to various treatment modalities.¹⁻³
- This study examined the impact of contingency management (CM) on longitudinal stimulant use heterogeneity across two 12-week clinical trials.
- We hypothesized that the CM effects on stimulant use would differ across multiple sub-groups (i.e., empirically estimated classes) of patients with distinct trajectories of stimulant use throughout the treatment period.

METHODS

- Data for this study came from two National Drug Abuse Treatment Clinical Trials Network studies - 0006 and 0007 (N=832).^{4,5}
- Both of the studies used for this investigation were randomized clinical trials comparing CM to treatment as usual in an outpatient psychosocial treatment setting (CTN 0006) and a methadone maintenance setting (CTN 0007).
- The primary outcome of stimulant (i.e., methamphetamine, cocaine, amphetamine) urine analysis (UA) was measured two times per week for 12 weeks for a total of 24 urines.
- We used GMM to estimate multiple latent class solutions (classes 1 through 6) examining the impact of contingency management on UAs over time, within each of the estimated classes.
- Consistent with previous statistical recommendations, the primary determinant (in addition to clinical interpretability, meaningfully sized classes, etc.) of model selection was the Bayesian Information Criterion (BIC; i.e., the smaller the better).⁶
- All models were estimated assuming a linear slope because initial model fitting indicated that the estimation of a quadratic slope decreased model fit and added unnecessary model complexity.
- All analyses were performed using Mplus 7.1.⁷

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RESULTS

- The best fitting, clinically interpretable model was the three class linear model (BIC=7624).
- Importantly, this model not only fit better than other multi-class solutions, but provided a better fit to the data than the single class model (i.e., assumes homogeneity of individual trajectories of change), which is the more common method of analyzing longitudinal substance use clinical trial data.
- Class 1 (21% of sample) = low probability (35%) of a positive UA (UA+) at baseline, steep decline in UA+ submissions during treatment, and CM caused a large decline in UA+ submissions over time (B = -0.32, p < 0.05).
- Class 2 (38.4%) = moderate probability of UA+ at baseline (42%), moderate decline in UA+ submission over time, and CM caused a moderate decline in UA+ submissions over time (B = -0.07, p < 0.05).
- Class 3 (41.6%) = high probability of UA+ at baseline (65%), increase in UA+ submissions over time and no effect of CM.
- See Table 1 for a detailed report of the class-specific parameter estimates and Figure 1 for observed and model estimated class-specific UA trajectories.

CONCLUSIONS

- Identifying sub-groups may help explain heterogeneity in substance use trajectories and identify characteristics that could inform treatment non-response (e.g., Class 3).
- Such models could also assist with identifying segments of the stimulant use population who could benefit from ancillary services in order to more effectively impact abstinence.

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Table 1. Growth Mixture Model Estimates for the Impact of Contingency Management on Twice Weekly Urine Analysis Submissions Across Three Classes.

Class 1 (21.0%)			
Covariates	Outcomes	Unstandardized Estimate	(95% CI)
Trial Arm →	UA Intercept	- 0.226ns	(- 0.811 - 0.358)
Trial Arm →	UA Slope	- 0.320*	(- 0.580 - - 0.060)
UA Intercept →	UA Slope	- 0.016*	(- 0.024 - - 0.008)
	UA Slope Mean	- 0.474*	(- 0.588 - - 0.360)
Class 2 (38.4%)			
Covariates	Outcomes	Unstandardized Estimate	(95% CI)
Trial Arm →	UA Intercept	- 0.226ns	(- 0.811 - 0.358)
Trial Arm →	UA Slope	- 0.077*	(- 0.115 - - 0.039)
UA Intercept →	UA Slope	- 0.016*	(- 0.024 - - 0.008)
	UA Slope Mean	- 0.075*	(- 0.107 - - 0.043)
Class 3 (40.6%)			
Covariates	Outcomes	Unstandardized Estimate	(95% CI)
Trial Arm →	UA Intercept	- 0.226ns	(- 0.811 - 0.358)
Trial Arm →	UA Slope	- 0.027ns	(- 0.057 - 0.004)
UA Intercept →	UA Slope	- 0.016*	(- 0.024 - - 0.008)
	UA Slope Mean	0.069*	(0.038 - 0.101)

UA = stimulant urine analysis. The dependent measure was a negative or positive UA across 24 possible urine analysis submissions (twice per week for 12 weeks; 0 = negative UA for stimulants, 1 = positive UA for stimulants). Trial Arm represents the two treatment groups (0 = Treatment as Usual; 1 = Contingency Management). UA Slope Mean represents the conditioned mean (i.e., intercept) of UA slope change during the 12-week clinical trials. ns = non-significant. *p < .05.

Figure 1. Observed and estimated positive UA trajectories modeled via growth mixture modeling across two contingency management clinical trials.

