SUPPLEMENT 1

First Stage of Modeling

A semi-parametric mixture quadratic growth model of suicidal thoughts and behaviors (STBs) was fit as a function of age, using a finite-dimensional approximation to Dirichlet Process Priors (DPP) Model.[1] In this model, the posterior distributions of unknown parameter were estimated based on a stick braking algorithm[2] in a Markov Chain Monte Carlo approach, using Gibbs sampling, implemented in WinBugs program. In this approach, we specified a large upper bound on the potential number of classes (20 was chosen as the upper bound). The number of latent classes was an unknown parameter having values from 1 to the chosen upper bound and distributed according to an intrinsic Poisson-like prior distribution.[3] The posterior mean of the number of classes was approximately 4 (posterior m = 4.15, SD = 0.37), which was used in turn as the number of latent classes in the subsequent modeling stages. This was also confirmed by fitting separate growth mixture models for each possible number of classes (2,3,4,5,6…), and using a version of the Deviance Information Criterion (DIC) to determine the best fit; DIC is a generalization of Akaike Information Criterion or Bayesian Information Criterion model fitting criteria for Bayesian inference.[4]

Second Stage of Modeling

A standard Bayesian group-based quadratic growth-mixture model was then implemented using MCMC with Gibbs sampling with only four classes, as estimated from the DPP model. To minimize the chances of identifying classes with small probabilities of estimated membership, we stipulated that latent classes would include at least 10% of the sampled population. This was incorporated into the model in terms of a Dirichlet prior distribution postulated for the class probabilities having concentration parameters (10,10,10,10), yielding a prior estimate (mean) of 0.25 for a participant belonging to each of the four classes. Growth parameters (intercepts and slopes associated with linear and quadratic polynomial terms) for each class and precision parameter associated with the STBs received independent and non-informative normal and a gamma priors, respectively. The MCMC simulations used 100,000 simulations for burn-in, and 1,000,000 simulations for convergence of the model.

Third Stage of Modeling

Using the information available from the second stage of modeling (i.e., the simulated values of class memberships and growth parameters), we predicted the relationships between class membership and covariates not used in the original estimate of latent classes of growth. To do this, we used 100 simulations (batches) for each participant, randomly chosen from the final 1,000 iterations satisfying the 10% constraint. Using generalized estimating equations, risk and protective factors and non-suicidal outcomes were modeled as dependent variables as a function of the simulated values of the class variables. A conservative approach was used in the modeling of longitudinal data, with sandwich (robust) variance estimates to provide additional protection against heterogeneity and departure from assumptions. Parameters estimated from these models were adjusted for within- and between-batch variability.

In secondary analyses, we examined the relationship between individuals' highest probability latent class trajectories (maximum a posteriori classification) and covariates. The results of analyses using participants' simulated class variables and those based on maximum a posteriori classification were similar; for this reason, only the former are presented in detail.

Supplemental References

1. Escobar MD, West M. Bayesian density estimation and inference using mixtures. J Am Stat Assoc. 1995;90:577-588.

2. Sethuraman J. A constructive definition of Dirichlet priors. Statistica Sinica. 1994;4:639-650.

3. West M. Inference in successive sampling discovery models. J Econometrics. 1996;75:217-238.

4. Celeux G, Forbes F, Robert CP, Titterington DM. Deviance information criteria for missing data models. Bayesian Analysis. 2006;1:651-673.