A Latent Profile Analysis of Substance Abuse, Violence, and AIDS Syndemic Variables and Relationship to Sexual Risk

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We will conduct advanced statistical analyses of data related to substance abuse, violence, and HIV/AIDS (so-called "SAVA syndemics") collected over time from men who have sex with men. The analysis will allow us to identify complex patterns about how the combination of these SAVA factors influence sexual risk behaviors, such as frequency of condomless sex and number of sexual partners. Such knowledge will help inform the development and implementation of sexual health and promotion programs and interventions.

Background

While the notion of the syndemic epidemic among substance use, violence, and AIDS has gained much momentum in recent years (Hart & Horton, 2017; Singer, 2009; Singer & Council, 2006), capturing the true nature of "syndemic" has remained elusive in statistical analysis. A common feature of a syndemic is the synergy of diseases and and exposure to risk. To date, quantitative measurement of any "syndemic" has been problematic as researchers have tended to either create a sum score of number of syndemic risk variables a person has experienced (see Tsai & Burns, 2015; Tsai & Venkataramani, 2016), or have entered SAVA risk variables into a regression equation (e.g., Sullivan, Messer, & Quinlivan, 2015)-—both miss the mark on the synergistic nature of syndemics. Occasionally, studies will enter multiplicative interaction terms into the regression equations (Stoicescu, Ameiiia, Irwanto, Praptoraharjo, & Mahanani, 2019), but such interactions are often underpowered (McClelland & Judd, 1993) and are still relying on linear relationships among the variables. Latent profile analysis, which does not characterize the syndemic construct as a continuous measure but rather as forming distinct categories or typologies of persons, may more readily capture the co-occurring nature of the SAVA syndemic by grouping people into underlying latent classes (or profiles for continuous variables) within a population. As a hypothetical example with three classes: a group of men at relatively low risk among all variables, a group of men who experience high childhood violence and current problems with illicit substances, a group of men who have experienced many violent events in their adult lives. Latent class/profile analysis falls under the broader "mixture modeling" heading (mix of sub-groups within a population) (B. Muthen, 2001, 2008). We feel that the HPTN 061 dataset is in a unique position to better understand the prevalence of the SAVA syndemic. A latent profile analysis should help clarify the make-up of these varying sub-groups according to risk status and the relationship of the group to later safe-sex practices. Identifying unique groups of individuals at varying levels of risk should help tailor prevention and intervention approaches to better curb the spread of HIV.

Specific Aims and Hypotheses

Among participants in HPTN 061, different latent profiles will differentially relate to sexual risk behavior. For instance, we would expect there to be one latent profile comprised of men at low SAVA risk. We would also expect this group to negatively relate to amount of sex without a condom a year later and number of sexual partners. We also expect different profiles of risk to emerge (e.g., men who have a childhood history of violence and heavy drug use in adulthood; men who are heavy alcohol users (but not illicit drug use) and highly depressed; etc.) and for these profiles to relate differently to the sexual risk outcomes. These hypotheses will be empirically tested.

Study Design and Analysis

We are proposing to use latent profile analysis (LPA) to better understand profiles of substance use, violence, and HIV/AIDS (SAVA) and the relationship to sexual risky behaviors among Black men having sex with men using the HPTN061 dataset. We will choose the final number of classes according to statistical fit using the Lo-Mendel-Rubin (LMR) Adjusted Ratio Test (Lo, Mendell, & Rubin, 2001 the bootstrap likelihood ratio test (BLRT) (Nylund, Asparoutiov, & Muthen, 2007), and the sample-size adjusted Bayesian Information Criteria (BIC), as well as sample size within profiles that captured theoretically and practically meaningful patterns. The BLRT, LMR, and sample-size adjusted BIC have been found to outperform other indices of fit in the context of latent class/profile analysis (Nylund et al., 2007; Tofighi & Enders, 2008). We will also examine entropy as an indication of ability to delineate class membership. Here, entropy with values approaching I indicate clear delineation of classes. (Celeux & Soromenho, 1996). While we are starting out more broadly by including a large number of variables, we will use the strategy identified by Dean and Raftery (2010; Raftery & Dean, 2006) to discard variables that provide little information (or even detract from) to the resulting classes and expect that much fewer variables than proposed will make up the final classes.

As a form of validating the final classes, the modified Bolck, Croon, and Hagenaars (BCH) approach (Bakk, Tekle, & Vermunt, 2013) will be used to examine differences in amount of condomless sex occurring in the preceding six months (using the last wave of data for the outcomes) and the number of sexual partners across class membership, Here, a Poisson or negative binomial model will be used to model these count outcomes (will the potential for zero-inflation depending on amount of zeroes in these outcomes). For the categorical demographic variables, the Lanza categorical approach was used. (Lanza, Tan, & Bray, 2013) In the formation of latent profiles, missing data was accounted for using full information maximum likelihood procedures. (Arbuckle, 1996). When examining differences across class membership, listwise deletion of variables was used. The Mplus statistical software package was used to perform the LPA and to test for differences across class memberships. (L. K. Muthen & Muthen, 2012)

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