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Editorial

Using Latent Profile Analysis and Related Approaches in Adolescent Health Research

In this issue of *Journal of Adolescent Health*, Giano et al. [1] use latent profile analysis (LPA) to examine how risk factors differentially combine to impact suicide risk among lesbian, gay, and bisexual youth. This article joins a fast-growing body of literature using statistical approaches to understand variability in adolescent health experiences. This editorial will focus on providing a brief review of how and when health professions researchers might use LPA or related methods in their own work [2,3].

LPA is one method in a family of statistical approaches called mixture modeling, which has been described in excellent lay-focused reviews by Lanza and Cooper [4] Oberski, [5] and Williams and Kibowski [6]. These methods focus on uncovering how adolescents and young adults can be similarly "grouped" or "profiled" on a combination of different variables. The idea of looking for "sets" of related factors is not a new idea in adolescent health. Researchers often want to know how the intersection of social, interpersonal, and environmental/structural influences may have impact on health outcomes. However, the method that we choose to investigate these questions will influence our understanding of how these variable effects are interpreted in the population.

Many people are familiar with *variable-centered* statistical approaches (e.g., multiple regression, factor analysis, and structural equation modeling) that focus on analyzing the relationship between a set of variables at the same time (e.g., if we entered multiple predictors into a regression model) [7]. An implication of this orientation is that we interpret a variable's average effect (e.g., using a regression coefficient's slope direction and magnitude) as being *the same for all members of the population* [8,9]. Any programming effort that results from variable-centered approaches must also assume this similarity. For example, within the framework of the present study, if researchers had used a variable-centered approach, the results would likely be translated into recommendations that all lesbian, gay, bisexual, and transgender (LGBT) youth should receive the same suicide prevention programming content because the whole population would be assumed to have relatively similar levels of suicide risk and should therefore all respond in the same way to content.

In many instances, this "one size fits all" assumption is not realistic. There are instances in which an aspect of a young person's experience (e.g., being a gender/sexual minority, being a person of color, and being incarcerated or being residentially unstable) and/or an intersection of these characteristics (e.g., being both a sexual minority youth *and* residentially unstable) can uniquely heighten an adolescent's vulnerability to (or protection from) an outcome [10,11]. This information allows for much more adaptable or tailored program delivery, as program design can focus on specific factors that are important *for that group* [12]. *Person-centered approaches* such as LPA address these needs by identifying subgroups or subpopulations—here called "profiles"—that classify participants into discrete groups who show similarity on chosen measures [5,6,9].

LPA provides two key pieces of information that allow us to better understand unique health experiences within a person-centered approach, which are (1) profile characteristics and (2) profile link to outcome [2,3]. *Profile characteristics* identify both the optimal number of profiles in a population, which tell us the extent to which risk is heterogeneous (more classes) or homogeneous (fewer classes) in a population, and the likelihood of each variable being associated with a given profile, which helps us derive the substantive "meaning" of each class. For example, Giano et al. [1] identified six unique profiles of risk factors for LGBT youth based on Youth Risk Behavior Survey measures of sleep, being bullied, alcohol use, poor grades, and electronics use. Class 6 was associated with the "highest risk" because of its association with the highest scores in all risk factors, whereas four other classes had mixed levels of risk based on their association of high- and low-risk score factors. *Profile link to outcome* provides information about how profile membership links to a higher or lower likelihood of experiencing the outcome variable of interest. Here, Giano et al. [1] establish that both the highest risk class (Class 6) and one of the mixed risk classes (Class 3) had a higher risk of suicide compared with the lowest risk class (Class 2). Such analyses permit a more focused youth-centered means of identifying what types of adversity to target to reduce suicide risk in this population. By using a person-centered (rather than variable-centered) analytic approach, the results can inform suicide prevention programs in ways that allow the development of

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more nuanced strategies for addressing the needs of LGBT youth based on profiles of varying risk.

Although an exhaustive review of LPA mechanics is beyond the scope of this work (earlier recommended citations provide excellent overviews), it is useful to briefly compare related methods and discuss when each application is used. The mixture modeling family include four primary "flavors," including LPA, latent class analysis (LCA), growth mixture modeling (GMM), and latent transition analysis (LTA). Both LPA and LCA seek discovery of unobserved "profiles" or "classes" (as described previously) when data are cross-sectional, although LPA is used when variables are continuous and LCA is used when variables are categorical. GMM and LTA are used when data are longitudinal; GMM is used with continuous data and when research questions focus on identifying group-based differences in change over time, whereas LTA uses categorical data to examine how profile or class membership shift over time [4]. All applications are flexible to the addition of proximal and distal variable additions and use a series of model fit criterion to choose the "best" option when multiple models are being compared [6,13,14]. As reviewed here, and in other publications [4–6], with careful attention to data structure and research interests, these four methods provide a powerful tool to better understand nuances in adolescent and young adult health.

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