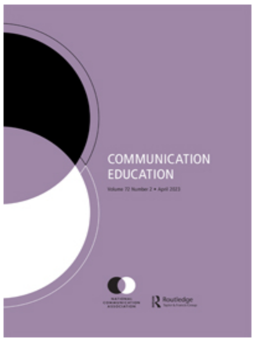

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# Mixture modeling: a person-centered approach to studying communication and learning

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Instructional communication scholars have traditionally adopted a process-product paradigm to estimate how teacher communication behaviors associate with student learning outcomes (Cortez et al., 2006). This traditional paradigm has generated much foundational research on effective teaching. At the same time, this approach might be appropriately described as narrow because it deemphasizes the fact that students are unique learners with their own roles, responsibilities, motivations, and abilities (and so on) that they bring into their learning environments. Substantively speaking, this process-product approach is limited because it overemphasizes the importance of how effective teaching, both principally and generally, fosters the *same* learning outcomes for all students in the *same* way (effective teaching is assumed to result in learning for all students despite their uniqueness in who they are).

Statistically speaking, process-product scholarship typically examines communication and student learning relationships using the general linear model (e.g., correlation, *t*-test, analysis of variance, ordinary least-squares regression). This paradigm takes a *variable-centered* approach when scholars associate communication variables with learning variables. Taking a variable-centered approach has been foundational to the discipline, but it assumes that students from a sample belong to a single population. Assuming that students come from a homogeneous population yields a single parameter estimate for a communication and/or learning association; that is, one statistical estimate will suffice for all students in a study. For instance, if an estimated correlation is $r = .30$, it is implied that this is the correlation for all students in the population. Similarly, in confirmatory factor analysis, if a factor loading is $\lambda = .88$, this is the estimated factor loading for everyone. A variable-centered approach places the emphasis on *variables* rather than *people* by providing single estimates that describe relationships between variables under study.

Alternatively, the analytical focus can be shifted from variables to *people* through the application of finite mixture modeling which offers a *person-centered* approach to studying communication and learning. Unlike a variable-centered approach, a person-centered approach allows for population heterogeneity to the extent that the sample embodies an unknown mixture of homogeneous subpopulations. In the truest application of mixture modeling (a direct application), the goal is to uncover latent

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(unobserved) subclasses of students in the population. In a more practical sense (an indirect application), mixture modeling simplifies (sometimes exceedingly) complex multivariate distributions of variables that are shared by relatively similar types of students. At its core, mixture modeling estimates a categorical latent variable (while accounting for measurement error) derived from relevant learning indicators (or communication patterns, or whatever a researcher wants to differentiate among people) that explains how students differ in the population. The goal is to uncover distinct subclasses of students and to determine how these classes differ with respect to specific research questions or hypotheses. This is a typological analysis because latent subgroups (classes or profiles) of students are assumed to differ meaningfully in how they might learn, communicate, or succeed in academic environments. After latent classes/profiles are identified, predictors (antecedents) of profile membership (the odds of belonging to a profile) and distal outcomes (consequences of profile membership) can be estimated.

To be clear, mixture modeling still uses variables as indicators during estimation, but as a person-centered approach, it focuses on groups of students differentiated by unique and distinguishable *configurations of indicators*, which is not the same as correlating one variable with another. In short, the use of mixture modeling recasts a greater focus on studying the student as a person and draws attention to relations among people rather than relations among variables. For cross-sectional designs, mixture modeling includes *latent class analysis* (LCA) for categorical indicators (e.g., "Do you intend to apply to graduate school"?) and *latent profile analysis* (LPA) for continuous indicators (e.g., "How many hours did you study for your final exam?"). In LCA, conditional response probabilities (the probability of a student endorsing an item in a given class) are estimated for categorical items (binary or ordinal items). In LPA, means and variances are modeled for the different profiles of students who share commonalities on continuous measurements (e.g., summed or averaged scale scores). Both categorical and continuous indicators may be combined in a mixture model. For longitudinal designs, classes and profiles of student learners can be modeled using latent transition analysis (LTA) and growth mixture modeling (GMM). LTA can characterize how students change classes over time (e.g., transitioning from a novice learner to an expert learner over time). GMM can identify how types of students might change differently over time (e.g., some types of students might learn at a very fast rate, whereas other types of students may struggle to learn throughout an entire course).

Researchers in the learning sciences have uncovered classes (LCA) and profiles (LPA) of students who meaningfully differ in their learning strategies, self-regulation, literacy, motivation, metacognition, test anxiety, academic emotions, achievement, and so on. For example, Fosnatcht et al. (2018) studied first-year students' hourly time expenditures during college and measured how they spent their time (1) preparing for class, (2) working for pay, (3) relaxing and socializing, (4) engaging in cocurricular activities and community service, (5) providing dependent care, and (6) commuting to campus. Using LPA, Fosnatcht et al. (2018) identified four profiles of first-year students: *balanced* (69% were typical students who spent their time divided by preparing for class, working, relaxing and socializing, and cocurricular activities), *involved* (12% were students who spent most of their time on cocurricular activities and volunteering), *partiers* (14% were students who spent most of their time relaxing and socializing), and *parents* (5% were students who spent most of their time caring for dependents and some of their time working). Modeling predictors of latent profiles, Fosnatcht et al. (2018) found that student-athletes were less likely to be *partiers* than *balanced* in their time-allocation profiles. Modeling distal outcomes of latent profiles, the researchers found that compared with *balanced* students, *involved* students engaged in more collaborative learning, had more student–faculty interactions, and had more discussions with diverse others. As highlighted by this example, adopting a person-centered approach to studying learning yields important differences for subgroups of students, and covariates can be modeled as antecedents or consequences of membership to further clarify who students are and what they do in college.

In summary, despite the discipline's traditional quantitative approach of investigating communication and learning from the standpoint that teachers impact students in a uniform manner, the use of mixture modeling relaxes the assumption of homogeneity so that learning does not have to be modeled as "one (effect) size fits all." Thus, we encourage instructional communication scholars to consider mixture modeling and to adopt a *person-centered* approach to studying communication and learning, as is done in other learning sciences (for a practical guide, see Hickendorff et al., 2018). When unobserved heterogeneity in the student population is considered, nuanced learning processes and outcomes may be illuminated. Mixture modeling, including LCA and LPA, and its longitudinal extensions such as LTA and GMM, uncovers hidden subgroups of students and reveals distinct effects in learning environments. That said, our discipline has much to gain by studying learning with a shift in focus to examining subgroups of students who collectively differ in their experiences of, and reactions to, their learning environments.

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## Disclosure statement

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