Calling for Equity-focused Quantitative Methodology in Discipline-based Education Research: An Introduction to Latent Class Analysis

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ABSTRACT

Mixture modeling is a latent variable (i.e., a variable that cannot be measured directly) approach to quantitatively represent unobserved subpopulations within an overall population. It includes a range of cross-sectional (such as latent class [LCA] or latent profile analysis) and longitudinal (such as latent transition analysis) analyses and is often referred to as a "person-centered" approach to quantitative data. This research methods paper describes one type of mixture modeling, LCA, and provides examples of how this method can be applied to discipline-based education research in biology and other science, technology, engineering, and math (STEM) disciplines. This paper briefly introduces LCA, explores the affordances LCA provides for equity-focused STEM education research, highlights some of its limitations, and provides suggestions for researchers interested in exploring LCA as a method of analysis. We encourage discipline-based education researchers to consider how statistical analyses may conflict with their equity-minded research agendas while also introducing LCA as a method of leveraging the affordances of quantitative data to pursue research goals aligned with equity, inclusion, access, and justice agendas.

INTRODUCTION

In this research methods essay, we join a growing number of education researchers who argue data are socially constructed—shaped by the researchers deciding *what* and *how* to research (Zuberi and BonillaSilva, 2008; Sablan, 2018; Buchanan *et al.*, 2021). Leaning on tenets of critical quantitative approaches (Zuberi, 2001; Stage, 2007; Covarrubias and Vélez, 2013; Stage and Wells, 2014; Tabron and Thomas, 2023), quantitative data and the statistical analysis used to understand data are not neutral but are filtered through the biases held by the individuals who create and conduct them. There are different approaches to critically engage in statistical analyses of quantitative data. Hernández's (2014) description of quantitative criticalism encourages researchers to define and make their particular approach transparent. For example, Gillborn and colleagues' (2018) application of Critical Race Theory to quantitative data and analysis includes five principles: "1) the centrality of racism; 2) numbers are not neutral; 3) categories are neither "natural" nor given: for 'race' read 'racism'; 4) voice and insight: data cannot 'speak for itself'; 5) using numbers for social justice" (p. 170).

Unfortunately, it is common practice that much research does not take up these tenets. For example, using White students as a reference group (and comparing them with non-White students) is a binary comparison that centers whiteness and can wrongfully position racial inequities as natural (Castillo and Babb, 2023). These tenets encourage researchers to recognize the risks of 'presenting a wholly social category as if it were a natural and fixed difference' (Castillo and Gillborn, 2022, p. 8). Creating a non-White group falsely infers that all individuals included in that category share enough of the same lived experiences to constitute a meaningful group for the study at hand. This tenent in particular underscores for researchers the importance of examining the limitations of the categories they include

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(Suzuki *et al.*, 2021). These categories are not limited to race. For example, researchers have centered tribal (Sabzalian *et al.*, 2021), queer (Garvey *et al.*, 2019), and trans (Curley, 2019) theory when trying to better understand variation. Common across these different approaches is the call for all researchers to make more thoughtful decisions about the questions being asked and how their data are analyzed. Some discipline-based education research (DBER) scholars have begun to take up these tenents, including the recently published essay in CBE-LSE by Pearson and colleagues (2022). In this essay, Pearson and colleagues advocate for the importance of integrating critical quantitative approaches in science, technology, engineering, and math (STEM) equity research and offer a series of self-reflective questions and recommendations intended to support the integration of critical approaches by DBERs engaged in quantitative STEM equity analysis.

There is no one right way to support more equity-focused research. This research methods essay contributes to this effort to support discipline-based education researchers to apply these tenents to their work by introducing and describing a particular quantitative method, latent class analysis (LCA), as one way to support anti-deficit, person-centered, and equityfocused research agendas in STEM education.

It is important to note that any given statistical method is neither inherently biased nor unbiased. It is through the application of a given statistical method that bias is introduced. As such, the aim of this essay is not to advocate for LCA as the only way to support anti-deficit, person-centered, and equityfocused research in STEM education. Instead, our goal is to introduce CBE-LSE readers to LCA by highlighting aspects of this statistical approach that equity-minded researchers could consider in their research. We provide an overview of LCA and a hypothetical example of how one could apply LCA in STEM education, including the types of research questions this method can support. Next, we describe the ways in which LCA can offer STEM education researchers prioritizing critical quantitative approaches a new way to explore variation in a population. Given our goal of increasing interest in LCA and illustrating ways in which this methodology can support equity focused efforts, we conclude this essay by highlighting publications discipline-based education researchers can refer to for a more technical tutorial on conducting LCA rather than including that level of detail here.

The target audience for this essay is DBERs interested in using equity-focused quantitative methodologies, though we recognize our intended audience may vary greatly in terms of experience using quantitative methodologies. Table 1 provides a glossary of terms to support readers unfamiliar with the terminology used throughout this paper. The definitions in the glossary represent how these terms are specifically used in this paper; alternative or more general definitions appropriate for other applications may exist.

Positionality Statement

Four of us (T.S., O.O.O., J.W.W., and L.L.W.) are early career DBERs who were selected to participate in an advanced quantitative methods training and mentorship program led by the last two authors (K.N.-G., M.I.) designed to advance the understanding of issues related to diversity, equity, and inclusion in STEM education (NSF Award 2224786). We are a diverse group of scholars in both a professional and sociocultural sense and vary in professional status, disciplinary training, and institutional contexts. While the individual research agendas and theoretical frameworks we employ differ, our conversations as a part of this program have revealed our shared value of quantitative research methods centered around an anti-deficit, person-centered, and equity-focused perspective.

Throughout our careers, the four of us have learned about quantitative analyses from different sources, including discipline-based education research journals, and our own reading of and conducting of equity-focused research. We are all interested in learning about different approaches researchers take to combine quantitative analyses and discipline-based education research focused on equity. This has led us to often wonder whether we need to sacrifice rigorous quantitative methods in the hopes of addressing equityfocused questions or to use traditional quantitative methods even if we found those to not be in concert with our values. Through specialized training, we were exposed to mixture modeling, an approach that could help us implement our equity-focused research interests in ways consistent with our values. We recognize that this methodological approach is one of many approaches to equity-focused research questions and like all methods, has the potential for misuse. However, we believe that this method could be useful to members of the STEM education research community interested in conducting equity-focused quantitative research through an anti-deficit, person-centered lens.

Description of LCA

LCA is part of a large set of quantitative models called mixture models (see Muthén and Shedden, 1999; Muthén and Muthén, 2000; Muthén, 2001; Muthén and Masyn, 2005; Masyn, 2013; Nylund-Gibson *et al.*, 2019). Mixture modeling is grounded in the fundamental concept of population heterogeneity, and assumes in any given population, differences exist among the individuals within that population. Mixture modeling methods rely on latent variables, which are variables that cannot be measured directly (e.g., attitudes, self-efficacy, mindset, etc.) to model the assumed population heterogeneity (Table 1). Because latent variables are inherently unobservable, they must be indirectly measured by a set of observable variables (commonly referred to as indicators; e.g., survey items) selected based on theoretical considerations. By maximizing both within-group homogeneity and between-group heterogeneity among that set of observable variables (or indicators), mixture modeling approaches identify unobserved (or

TABLE 1. Glossary of terms used throughout this essay

Term	Definition
Between-group	exploring variability between groups (e.g., across different genders)
Categorical variable	a characteristic that can be binned into separate groups (e.g., gender, attitude, final letter grade, etc.)
Class enumeration	the process of selecting the appropriate number of classes in mixture modeling, including a latent class analysis (LCA), based on several indicators, including statistical indicators (e.g., information criterion and likelihood-based comparisons), classification accuracy, and the motivating theoretical background
Conditional probability	a value that ranges from 0 to 1 that describes the average probability that a person in a given latent class (or group) will endorse a given observed variable (indicator). These are the values often used to create the profile plots.
Continuous variable	a characteristic with numeric values typically ranging from a minimum to a maximum value, a nondiscrete variable (e.g., temperature, height, age, etc.)
Covariate	an observed predictor variable that is thought to be related to the emergent latent classes (e.g., student characteristics, SAT/ACT scores, prior experiences, etc.)
Distal outcome	a variable that is conceptualized as a consequence of membership in a specific latent class (e.g., final course grade, persistence in STEM courses)
Heterogeneity	characterized by being different or diverse
Homogeneity	characterized by being the same or of a similar kind
Indicator variable	an observed variable or measure (e.g., survey item) that is used to characterize the latent class variable. For LCA, these indicators are assumed to be categorical variables (e.g., engage in a specific behavior or not)
Latent class (or group)	a grouping of individuals based on the set of response patterns of the indicator variables
Latent variable	a variable in the statistical analysis that is not directly observed but can be measured using a set of indicator variables (e.g., attitudes, self-efficacy, depression, etc.). Latent variables can be continuous variables or categorical variables
Person-centered approach	research method that focuses on grouping individuals rather than grouping items that measure a particular construct or factor. In LCA, we focus on individual response patterns instead of individual items
Within-group	exploring variability within the same group (e.g., differences that exist among a group of women students)

latent) subgroups in a dataset. As such, the number of latent classes (also known as groups) in a population is commonly not known before conducting mixture modeling analyses, and it becomes the job of the researcher conducting the analysis to justify the number of latent classes present in the population by choosing the best-fitting model, a process referred to as class enumeration.

Similar to factor models, mixture models can accommodate both continuous and categorical observed indicators (e.g., survey items) to identify a categorical latent variable of interest. When models use continuous, measured indicators to estimate the categorical latent variable, models are referred to as latent profile analysis (LPA) models, whereas models with categorical observed variables (most commonly binary) are LCA models.

The main differentiation between more commonly used latent variable models and mixture models is that the latent variable is categorical, as presented in Table 2. The rows of the table differentiate the nature of the observed variables (e.g., survey data, etc.) and the columns differentiate the nature of the latent variable (categorical or continuous). For example, factor analysis and item response theory both estimate continuous latent variables using either continuous or categorical observed data whereas mixture modeling methods such as LCA or latent profile analysis estimate categorical latent variables.

Mixture modeling approaches are similar to commonly used clustering approaches such as k-means clustering (Beijie *et al.*, 2013). Both mixture modeling and clustering approaches identify clusters, or groups of people, that are characterized by being homogenous within a cluster while maximizing heterogeneity across clusters. Unlike clustering approaches, mixture modeling approaches take a model-based approach to clustering (Nylund *et al.*, 2007; Nylund-Gibson et al., 2019, 2023; Nylund-Gibson and Choi, 2018), which is advantageous because it provides ways to evaluate model fit and is reproducible.

A Hypothetical Application of LCA

To help highlight the utility of mixture models in DBER research, imagine we are interested in the variation of student behavioral engagement across gateway STEM courses at a research-intensive university and how it relates to course performance (e.g., course grade). A typical research question may compare engagement and course performance across different ethnicities. However, doing so may overlook variation within different ethnic groups that relate to course performance. Another way to explore variation is to model the variation in engagement within our population (and subpopulations) using LCA.

Consistent with this alternative research aim (i.e., to explore the nuanced ways in which students' engagement may differ), we can use LCA to address the following research question: What are different types of student engagement profiles that relate to course performance?

TABLE 2. Contextualizing mixture modeling alongside other latent variable models

	Latent variable	
	Continuous	***Categorical***
Observed Data		
Continuous	Factor analysis	Latent profile analysis (LPA)
Categorical (binary, ordinal)	Item response theory, ordinal factor analysis	Latent class analysis (LCA)

To explore engagement profiles, we could use five binary indicators to measure engagement (Table 3; Fredricks *et al.*, 2004). LCA helps identify groups of individuals that share a set of engagement characteristics that are different from engagement characteristics of other groups (Figure 1). Based on their responses to all five items, each individual in our sample is assigned a conditional probability value of belonging to each group or class (k). Because the number of latent classes in our population is unknown, we vary the number of classes (e.g., k = 1–5) and evaluate the performance of each model using a variety of statistical indicators along with our theoretical framework to determine the optimal value for k.

For the sake of our example, let us say three classes (k = 3) is determined to be the most supported model solution. Each student is assigned probabilities of being assigned to each of the three classes. By visualizing the average conditional probability scores of each class for each item in our hypothetical model (Figure 2), students in Class 1 had a pattern of high responses of "Yes" for all four items, and we would name this class "All Around Engagers." Students in Class 2 only had a pattern of high responses of "Yes" for engaging in behaviors outside the classroom, so we would name this class "Out-ofClass Engagers." Students in Class 3 only had a pattern of high responses of "Yes" for engaging in behaviors within the classroom, so we would name this class "In-Class Engagers." The selection of names of the classes in this example was informed by the patterns observed in the conditional probabilities. Care must be taken when naming classes to ensure they align well with these observed patterns, accurately reflect the heterogeneity captured by the classes, and are related to existing theory or literature.

We can then relate these classes to students' final course grade. Perhaps we discover In-Class Engagers have significantly lower final course grades than All Around and Out-ofClass Engagers. This insight provides us with potential areas of intervention to address in our STEM gateway courses. Understanding different types of engagement patterns among different groups of students with a variety of experiences, identities, and realities may provide methods in which we can offer targeted support. This support is more nuanced in that it helps to focus attention beyond comparing students based only on observable characteristics such as gender or ethnicity.

Applications of LCA in STEM Education Research There has been an increase in LCA use by educational and psychological researchers (Denson and Ing, 2014; Chan *et al.*, 2021; Mayworm *et al.*, 2023) across a wide range of educational contexts. Despite its utility, LCA has limited uptake within STEM education research. One example within STEM education is research by Godec and colleagues (2022) who used LCA to explore patterns in the participation of young students in informal science education. Using survey responses from 1624 participants, LCA identified subgroups of students' participation in informal science education. The researchers concluded that although students from minoritized groups rarely participated in informal science education activities, they expressed interest in STEM fields. The students from nonminoritized groups participated in informal science education activities regularly, regardless of their interest in STEM. While there is growing interest in this modeling approach from discipline-based education researchers working in the fields of biology (Tobler *et al.*, 2023), chemistry (Brandriet *et al.*, 2018), and physics (Chen *et al.*, 2021; Palmgren *et al.*, 2022), LCA has had limited use in equity-focused STEM education research.

In another example from STEM education research, in their article published in CBE-LSE titled "Identifying Faculty and Peer Interaction Patterns of First-Year Biology Doctoral Students: A Latent Class Analysis," Jeong and colleagues (2019) used LCA to understand patterns in graduate students' interactions with faculty and peers. Jeong and colleagues' research was informed by the graduate socialization theory, which posits that both faculty and graduate student peers act as socialization agents that impact a graduate student's cognitive and affective experiences as well as academic outcomes (Weidman *et al.*, 2001; Austin, 2002; Gardner, 2007). Instead of comparing socialization patterns in terms of gender or ethnicity, Jeong and colleagues used LCA to identify socialization patterns among 336 doctoral students who completed an 8-item scale modified from a socialization questionnaire (Weidman and Stein, 2003). The LCA model identified four distinct classes characterizing patterns of graduate students' interactions with faculty and peers as displayed in Figure 3. The four classes were differentiated in who they socialized with and what they socialized about (e.g., field-related work or personal life). The two largest classes were a group of students who socialize with faculty and peers about academic and personal needs (C1, 42%) and those who socialize with their peers mainly on both academic and personal need (C2, 41%). The smaller two classes consisted of students who only socialize with their peers on social/personal matters, not work related (C3, 9%) and those who socialize with both faculty and peers on field-related academic matter (C4, 8%). Based on the conditional item probabilities, Jeong *et al.* (2019) created class names as labeled in Figure 3.

Previous research had suggested graduate student socialization varies in terms of demographic characteristics such as gender, ethnicity, and international status. Therefore, the asso-

TABLE 3. Example student response data to five binary (Yes = 1 or No = 0) items that measure engagement

Student	Have you asked a question in class?	Have you answered a question in class?	Have you attended the optional review sessions?	Have you attended office hours?	Do you have a study group?
Student A	Yes (1)	Yes (1)	No (0)	Yes (1)	Yes (1)
Student B	No (0)	No (0)	No (0)	Yes (1)	Yes (1)
Student C	No (0)	No (0)	No (0)	Yes (1)	No (0)
Student D	Yes (1)	No (0)	Yes (1)	No (0)	No (0)
Student E	Yes (1)	Yes (1)	No (0)	No (0)	No (0)
…					
Student Z	Yes (1)	Yes (1)	Yes (1)	Yes (1)	Yes (1)

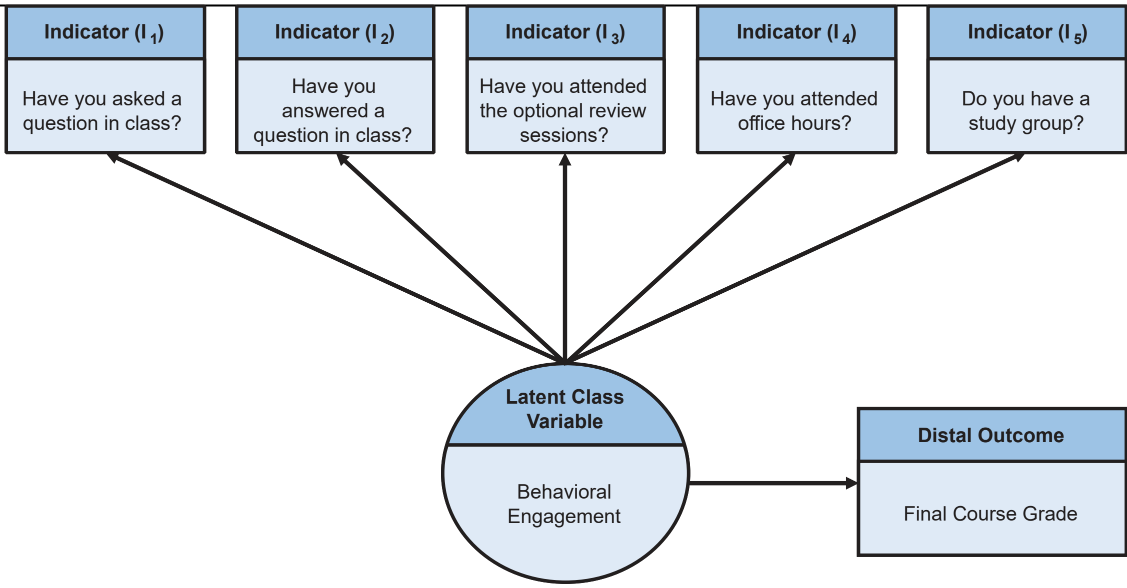

FIGURE 1. Path diagrams are often used to visually represent mixture models. In our path diagram, the observed data (student responses to our four binary items drawn from Fredricks *et al.*, 2004; Table 3) are the indicator variables (I_1–I_5) serving to indirectly measure the categorical latent variable (i.e., student behavioral engagement). Because the indicator items in LCA drive the emergent classes, these items should be strongly informed by the research's theoretical framework.

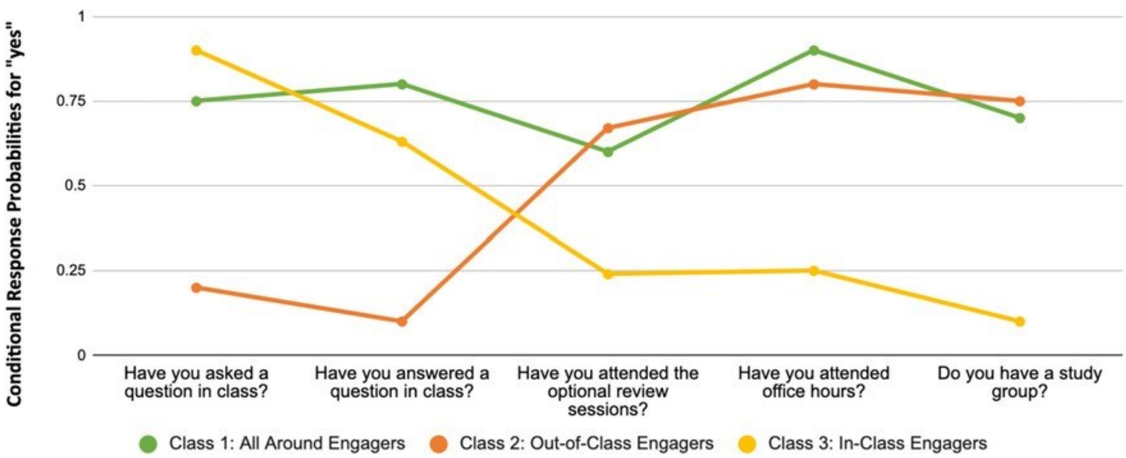

FIGURE 2. Conditional item probability results for the three class LCA model of behavioral engagement.

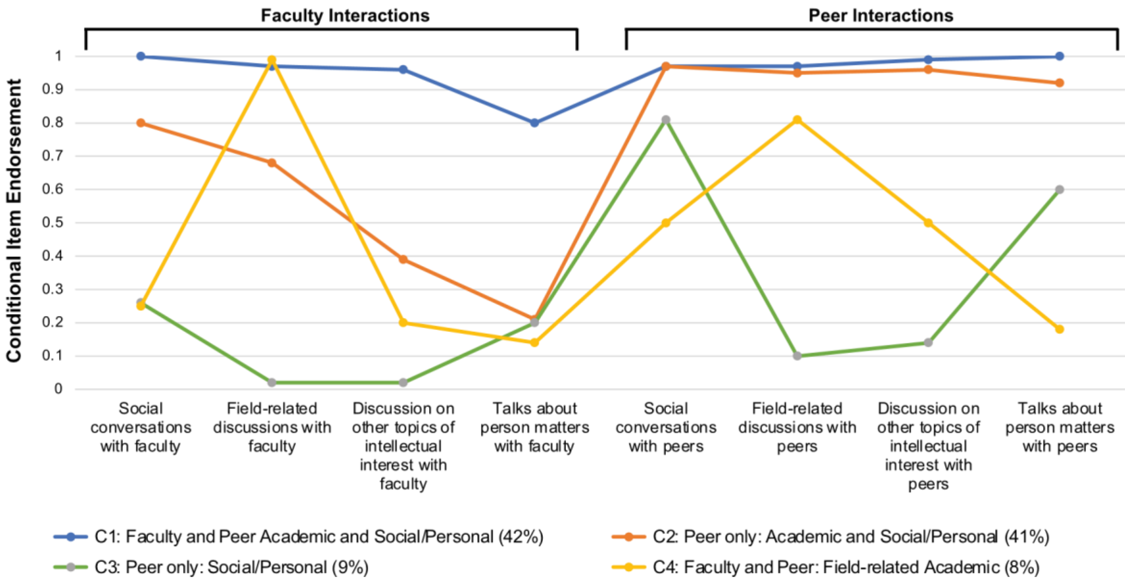

FIGURE 3. Recreation of a figure from Jeong *et al*. (2019) illustrating the identified 4-class solution of Student Socialization with their Faculty and Peers. Patterns of item endorsement were used to inform the naming of each class (C1–C4).

ciation between demographics and the four identified socialization classes was evaluated after the groups were identified. Additionally, the researchers selected eight student outcomes based on the socialization theory to examine the impact of socialization on graduate students. The authors pointed out that domestic students were spread across the four classes, while international students were more limited to field-related academic interactions and personal relationships exclusively with peers, suggesting inequities in their doctoral socialization experience and highlighting the potential for departmental interventions in graduate student training.

By employing LCA, Jeong and colleagues (2019) captured the mosaic of interactions graduate students engage in while also positioning their findings in a way that frames socialization through the lens of individual graduate student experiences. As a person-centered approach, LCA highlighted various ways in which graduate students socialize. Rather than relying on sociodemographic characteristics to compare students' socialization, LCA is one approach in which the unobserved variation in how students' socialize can be better understood. This approach is just one way to build on existing literature by offering a student-centered vantagepoint.

Affordances of LCA for STEM Education Research Understanding the unobserved patterns of variation within a population provides researchers deeper insight into the heterogeneity that is assumed to exist within a population. This insight can provide a more nuanced understanding of the complexities of a population with respect to measured outcomes. In the hypothetical example above, exploring patterns of student engagement revealed nuances of student behaviors that other statistical approaches may have masked. An alternative approach could be to sum student responses to our five survey items and calculate an engagement score, which could then be used to categorize students as "high" or "low" engagers. This approach would require identifying an appropriate threshold to guide the sorting of high and low engagers, which raises questions around the appropriate location of the cut point. Further, this approach provides little information about potential differences in the ways that students engage that could be productive. For example, say we used a behavioral engagement cut score at the value of 2 (with individuals scoring 2 or lower being labeled as low engagers and individuals scoring 3 or higher being labeled as high engagers). In this scenario, the In-class Engagers previously identified through LCA would be labeled as low engagers (Figure 2) despite engaging in a manner many educators and researchers would consider favorable (i.e., asking and answering questions in class). LCA can provide meaningfully distinct types of engagers, whereas the summing student responses to the survey items reflect a single dimension of students' engagement.

LCA allows us to make visible the variation in our population by retaining and embracing variation across our range of indicator variables (i.e., survey items). By characterizing patterns of behavioral engagement, we are able to describe the distinct ways in which students in our three groups (e.g., All Around Engagers, In-Class Engagers, and Out-of-Class Engagers) engage with the course—evidence which has direct implications for further analyses (as discussed in the following sections) as well as pedagogical decisions (e.g., incentives for classroom participation, using permanent group structures during class to provide additional study group opportunities, strategic scheduling of optional review sessions, etc.).

The intent of LCA is to uncover groups of *individuals* who are similar with respect to their responses to the set of observed measures (e.g., survey items). As such, mixture modeling is often described as a *person-centered* approach, where the research questions focus on grouping individuals instead of *variable-centered* approaches that aim to explore constructs (e.g., factor analysis) and then study how those constructs relate to each other (e.g., structural equation modeling). Moreover, the categorical nature of the latent variable provides a natural context to study subgroup differences and to compare experiences, characteristics, and outcomes across subgroups, which can be directly relevant to equity-focused research (see section below for details).

Many statistical approaches common in DBER require researchers to create groups in terms of categorical variables (e.g., using an instrument to sort students into "fixed" or "growth" mindset, sorting students into "high" or "low" selfefficacy groups, etc.). Creating these groups requires that researchers make a series of somewhat arbitrary decisions, typically relying on their own pre-existing knowledge of the context. It is also the case that these groups may be created out of convenience or by applying subjective cut points. Continuing with our example, if we were to evaluate the behavioral engagement of students with respect to course performance by creating two groups of students based on the number of survey items they identified with (i.e., high and low engagers), the variation in what engagement looks like for students would not be captured. Using a LCA approach, the nuances in the ways students engage could be better described. The results of the LCA (i.e. the number of groups, assignment of the most likely group membership of each individual, etc.) are based on a model-based approach, which affords the researcher a range of evidence-based tools to evaluate and guide what could easily be perceived as arbitrary decisions.

Using LCA to Support Equity-focused STEM-Education Research

So often in STEM education, demographic group comparisons position one group as the norm against which all other groups are compared (Castillo and Babb, 2023; Van Dusen and Nissen, 2020). The normative group is typically the most privileged group; comparing other groups with this group perpetuates a deficit orientation, where there are disparities in outcomes or achievements. For example, research that compares course outcomes across different ethnic groups (where ethnicity is treated as a mutually exclusive categorical variable such as White, Asian, Black, Hispanic, or Other), may wrongly attribute inequalities to racial differences, overlooking other important structural and institutional factors such as the quality of instructional opportunities that contribute to such outcomes or the variability within these race categories. Additionally, this approach of comparing groups in terms of demographics often ignores intersectionality, not acknowledging the multiplicative relationship of students' overlapping and multiple identities. Further, treating socially defined demographic groups as homogenous risks unidimensional and essentializing conclusions about student groups (i.e., believing all students who identify as belonging to a particular demographic group will share comparable lived experiences, beliefs, and identities).

LCA can help us understand variation within demographic groups in a way that has the potential to shift our focus away from "gap-gazing" practices (Gutiérrez, 2008; Young *et al.*, 2018), which are common in STEM education research (Metcalf, 2017). Rather than comparing groups, LCA can support analyses that explicitly model variation within groups. For example, returning to our hypothetical example of using LCA to examine behavioral engagement, perhaps we are interested in the distribution of first-generation students across the three behavioral engagement classes. By including first-generation status as a covariate in our model, we can regress the latent class variable on first-generation status to explore the variation in behavioral engagement within our first-generation student subpopulation. As a result, we could reveal patterns that indicate not all first-generation students need to engage in similar ways in order to be successful in a gateway STEM course.

As another example, research focusing on Black girls' experience in mathematics (see, e.g., Young and Cunningham, 2021) considers constructs such as student identity, selfefficacy, and interest. These researchers were particularly interested in exploring the variation among these constructs for this particular group of students (Black girls) rather than comparing their experiences to other groups. They argue that this person-centered approach is necessary because Black girls experience both gender and racial biases in STEM settings (Young and Cunningham, 2021, p. 29), thus the methodological choice needed to acknowledge and respect these intersecting identities (Young and Cunningham, 2021, p. 38) without situating those experiences (or their academic outcomes) in a contrasting lens comparing results to other demographic groups.

Another example is research that warns against collapsing subgroups of Asian Americans into a single group rather than considering the variation within this group (see, e.g., Teranishi, 2007). With over 40 ethnic subgroups who speak over 300 languages, this research argues there is significant variation among Asian Americans regarding factors such as culture and history (Teranishi *et al.*, 2004; Takaki, 2012; Lee, 2015). There is also variation among Asian Americans regarding achievement and higher education access (see, e.g., Lee, 1994; Museus *et al.*, 2013 Thus, collapsing all Asian Americans into a single group misses important variation among the groups. By embracing and intentionally modeling this withingroup variation, LCA is one approach researchers can use to explore potentially theoretically meaningful latent groups that otherwise remain hidden under more traditional, variablecentered approaches (i.e., grouping students based on demographic variables).

Despite the affordance of using LCA to support equityfocused research, we caution that the method in and of itself does not automatically address issues of equity and in fact, could be used inappropriately. Suzuki and colleagues (2021) identified three moments in quantitative methods more generally, and mixture modeling specifically, where researchers make decisions that influence the appropriate application of quantitative methods to advance toward an anti-racism agenda. The three moments include: "1) development of the research question(s) and identification of analysis variables; 2) decision-making about the role of race in planned analyses; and 3) interpretation of the results through a theoretical framework" (Suzuki *et al.*, 2021, p. 543). While Suzuki and colleagues' article focuses specifically on race, they encourage researchers to consider how similar decisions could be made with other quantitative research methods and other characteristics such as gender identity.

Limitations of LCA

Mixture modeling is a relatively new approach in education research and recommended best practices are still evolving (Nylund-Gibson and Choi, 2018). There are few courses available for graduate students, and many of the training options available are expensive (ranging from \$500–\$3000 per course). Even for those with the resources to attend training, and with some quantitative research experience, implementing mixture modeling may be intimidating. The learning curve for latent class analysis requires reading publications commonly found in more methods-focused journals rather than DBER journals. Even if researchers are able to run models, there are many decision points in the process that require researchers to not only follow best practices but be guided by their theoretical framework. For example, researchers must holistically evaluate the models by considering statistical fit information, the characteristics of resulting classes, and the statistical accuracy of the results (Muthén, 2003). Interpretation of the classes, including naming the classes based on patterns in the conditional item probabilities for the indicator items, requires the researcher to draw heavily on the researcher's theoretical framework (Lanza and Rhoades, 2013). Thus, there are several barriers to the use of this modeling approach for discipline-based education researchers, coupled with the ongoing development of the most current recommended practices based on resources they typically do not have access to.

Mixture modeling necessitates datasets large enough that are able to adequately capture the heterogeneity in a population. While there are no concrete rules around the required sample size, it has been recommended that to be confident in modeling solutions, sample sizes should be at least 200–300 (Nylund-Gibson and Choi, 2018), ideally at least 500, which may serve as a barrier to some DBER scholars. Without sufficient sample size, rare classes (e.g., small in relative size) can remain cryptic and hard to identify, especially if the overall sample size is small (Morgan, 2015). Additionally, while mixture modeling is a person-centered modeling approach which allows for under-represented individuals to be characterized by their set of item responses, it cannot solve for a lack of representation in the data. That is, when a particular demographic group is poorly represented in the data, heterogeneity unique to that group may not be distilled and thus mixture modeling does not help dismantle marginalization in these circumstances. However, unlike variable-centered approaches, in which data from poorly represented demographics are removed, mixture modeling retains data from these students to build models and seek solutions across all students, thereby retaining the voices and opinions of these marginalized students as part of the larger student population.

Suggestions for Researchers Interested in Exploring LCA

This paper is an exposition of the affordances of LCA and its promise in equity-focused STEM education research. As a way of introduction to mixture modeling, we focus only on LCA which is a cross-sectional model. The larger mixture modeling framework, however, includes a wide range of other approaches, including cross-sectional (a snapshot of a single point in time) and longitudinal models. Interested researchers should consider the family of mixture models to determine which method will best apply to the given research questions.

We hope that after reading this paper, DBER scholars will be prompted to want to learn more about LCA and mixture modeling. While this paper does not serve as a "how-to" guide that offers step-by-step instructions to complete LCA or mixture modeling, there are a range of books and peer-reviewed articles that describe more practical steps for applying this approach. For example, Nylund-Gibson and Choi (2018) answer 10 frequently asked questions about the application of LCA, including examples and code that can be used as a starting point to estimate LCA models. There are also many examples in different substantive areas of research (see, e.g., Lanza and Rhoades, 2013; Nylund-Gibson *et al.*, 2023). There are also opportunities to learn more through virtual or in-person training programs or professional development at conferences. Latent class models are becoming more widely used in a range of disciplines and quantitative scholars studying the use of mixture models, including LCAs, and the recommendations about best practices and specification are still being developed. We encourage DBER scholars interested in LCA to stay current with best practices by following the mixture modeling literature and to consider collaborating with quantitative methodologists current with the developments in best practice recommendations.

Concluding Remarks

LCA, and the related family of mixture modeling more broadly, represents a statistical approach that provides the opportunity to explore heterogeneity in a population that would otherwise not be observed. While LCA can be used for equity-focused quantitative analyses, like any quantitative method, learning how to apply the method in ways that are consistent with theory that are also in concert with the statistical best practices requires thought and careful attention. Like any quantitative approach, these methods are not immune to the biases and assumptions that any individual researcher brings to the task. Taking steps to increase our awareness of our own biases and assumptions and making these transparent throughout our process is one way in which we can all work toward equity-focused use of quantitative methods.

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