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A Quantitative Analysis Method for Feminist Researchers: A Gentle Introduction

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(2004) Paper No. 414

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A Quantitative Analysis Method for Feminist Researchers: A Gentle Introduction

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A portion of the research reported here was funded by a grant (1 R01 HD38530-01A1) from the National Institute for Research in Child Health and Development awarded to Sumru Erkut and Allison Tracy at the Center for Research on Women. A detailed description of the examples used in this paper, as well as Mplus program code used in these models, can be obtained by contacting the first author (106 Central St., Wellesley, MA 02481, atracy@wellesley.edu).

Suggested Citation: Tracy, A. J. and Sorsoli, L. (2004) *A Quantitative Analysis Method for Feminist Researchers: A Gentle Introduction*. (Wellesley Centers for Women Working Paper No. 414). Wellesley, MA: Wellesley Centers for Women.

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Abstract

Historically, quantitative and qualitative approaches to research have represented two sides of a philosophical divide among social scientists. Feminist researchers have traditionally invoked qualitative methods, embracing the ways they emphasize the reflexive, subjective nature of human experience. And yet, many recognize that what makes a feminist method "feminist" is not in the method itself, but in the way it is applied (Cook & Fonow, 1990). This paper provides a conceptual overview of a newly available modeling approach called latent variable mixture modeling (LVMM: Muthén, 2001), which we recommend for quantitative feminist research. The strength of this approach is that it preserves essential qualitative differences in experience while utilizing the breadth and statistical power of large sample data analysis, thereby combining strengths of both the qualitative and quantitative analytic paradigms.

Two illustrative examples are provided to demonstrate the usefulness of LVMM, one highlighting heterogeneity in relationships among items thought to measure the same construct and the other illustrating heterogeneity in relationships across different constructs in a model. Follow-up qualitative analysis with individuals representing extreme and typical cases is recommended as a way to verify results and generate new hypotheses. Implications of this approach for feminist research and for social policy and intervention efforts are discussed.

Introduction

Feminist research methods arose from a historical backdrop in which women, women's experiences, and subjects of interest to women had routinely been excluded from scientific studies; few women held positions as researchers; and the form research questions took and the ways results were interpreted tended to reproduce commonly held stereotypes or assumptions, thus helping to maintain the denigrated status of women. Against this backdrop, feminist researchers struggled with the idea that women, as a group, shared a set of experiences and a "way of knowing" that set them apart from men (Belenky, Clinchy, Goldberger, & Tarule, 1986), while also uniting them as a single oppressed group whose needs and experiences were deserving of attention and study. At the same time however, feminism itself (as a political movement) was being strongly criticized for attempting to create a "common identity" for women, seeking common ground while overriding or ignoring important and very real differences shaping women's lives and experiences due to race and/or class (Lorde, 1984; Scott, 1996; Walley, 1997). As Lorde (1984) argued, "White women focus upon their oppression as women and ignore differences of race, class, and age. There is a pretense to a homogeneity of experience covered by the word sisterhood that does not in fact exist" (p. 116).

The focus of feminist epistemology, meanwhile, was to analyze and critique traditional sources and systems of knowledge as well as to construct alternatives (Hughes, 1994) – for, as Lorde (1984) writes, "the master's tools will never dismantle the master's house" (p. 112). Feminist researchers were keenly aware that reliance on aggregate statistics, such as means and covariance structures, captured only the most typical experiences in the sample while "disappearing" experiences less typical. In effect, the reliance on aggregate data reproduced the very "common identity" that had created such controversy within the feminist movement. Thus, from the beginning, feminist researchers have felt that information gathered about women should simultaneously honor difference and the complexity of human experience, while being both morally responsible and respectful of research participants. To this end, feminists embraced approaches used in fields such as anthropology and sociology and in certain concentrations within the field of psychology, advocating that research begin with qualitative interviews and/or observation rather than the kinds of quantitative measurements that had become the standards for scientific research. Some feminists even suggested that in-depth qualitative interviewing was the "best" way to find out about women's lives (Oakley, 1981) and interviewing quickly became the "principal means" by which feminists sought to engage in data collection (Graham, 1984, p. 112). Perhaps because of the continuing emphasis on "voice," feminist research has become most closely associated with qualitative methods, which tend to rely on narrative rather than numerical data and offer a multitude of ways to listen carefully to subtleties of speech, emphasize the relational nature of research, and attend to power differentials and cultural context: innovations that have come to define a feminized approach to research (Letherby, 2003; Ramazanoglu & Holland, 2002; Way, 2001).

Unfortunately, the intensive and in-depth nature of the data collection and analysis procedures associated with qualitative research is only feasible with limited sample sizes, often fewer than 50 participants. A common critique of such small-scale studies is that the results may not generalize well beyond the bounds of the study sample. Although some researchers downplay the role of generalizability as a primary goal of their

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research, the influence of study results on broad public policy frequently hinges on a demonstration of the applicability of the findings to a much larger subpopulation of society. Indeed, evoking large-scale shifts in social policy is a primary focus of feminist activism and thus, the tension between the need to generalize experiences that would unify groups whose experiences indicate strong, undeniable, and coherent need for societal change and the need to attend to true heterogeneity of lived experience still exists for feminist researchers even today.

We hold that what makes a research method "feminist" goes beyond the purpose of the research, the questions asked, or the population served and extends to a particular approach and orientation to research. As Letherby writes, "It is important to stress that it is not the use of a particular method or methods which characterizes a researcher or project as feminist, but the way in which the method(s) are *used*" (Letherby, 2003, p. 81). In this way, we view both quantitative and qualitative approaches to social science research to be potentially powerful tools for feminist inquiry. Indeed, triangulation of research results across qualitative and quantitative studies greatly strengthens the external validity of the findings. However, in cases where quantitative and qualitative findings disagree, integration and interpretation of results across these two disparate research paradigms can be difficult (Maracek, 2003). Discrepant results may stem from differences in studies in terms of sampling frame, the social context of the data collection protocol, the operationalization of the constructs under study, the conceptual model, and/or assumptions underlying the analysis itself.

In an effort to capitalize on the strengths of both approaches and to facilitate cross-method interpretation of results, there has been an increased emphasis on the use of mixed method approaches that utilize sequential, coordinated substudies to address and refine a given research question. For example, Spencer, Porche, & Tolman (2003) explored the relationship between a gender equitable environment and educational and psychological outcomes by combining survey responses with classroom observations, focus groups, and interviews, using discrepant results from the differing methods to reach complex understandings of the experience and effect of equity within school environments. Still, sequential mixed method approaches continue to rely on embedded substudies that may require different sampling frames, different modes of data collection, and different analytic assumptions. Thus, even with a coordinated mixed method approach, findings from two or more substudies may lead to different conclusions that reflect methodological as well as substantive distinctions.

Fortunately, recent advances in statistical modeling estimators (Muthén & Shedden, 1999) have made it possible to combine elements of both the qualitative and quantitative analytic paradigms into a single analytic model. Models using this new statistical framework, known as latent variable mixture modeling (LVMM: Muthén, 2001), allow for the preservation of individual "voices" that are present in the data while also affording generalizability through the parametric modeling of these individual differences both within and across diverse subpopulations. In this way, models based on the new framework resolve some of the tension between traditional quantitative and qualitative data analysis paradigms in the analysis of large sample data.

A New Approach – Latent Variable Mixture Modeling (LVMM)

The separate terms in the phrase "latent variable mixture modeling" tell the story of what this approach is designed to accomplish. In statistical modeling jargon, the term "latent" refers to a construct that is not directly seen or assessed but is instead inferred from the data. For instance, individual items in a scale each may capture only a small segment of an underlying (latent) construct, but when combined, the depth of the construct is well captured. Therefore, the essence of the latent construct is revealed only when considering the full set of items as a whole.

The term "variable," simply put, means a construct that can take on more than one value. It is important to distinguish, in this modeling context, whether the values the variable takes are ordered along a continuum (e.g., scores on a competency test) or represent unordered categories (e.g., random assignment to one of three groups). These two types of variables reflect quantitative individual differences, in the former case, and qualitative differences, in the latter.

The term "mixture" in the context of statistical modeling refers to the idea that there are multiple subpopulations hidden in a set of data. In other words, the frequency distributions of the variables are a result of the "mixture" of distributions obtained from multiple heterogeneous subpopulations. Most traditional statistical techniques require the assumption of a single homogeneous population from which the sample is drawn, unless the subpopulations are known, categorized prior to analysis, and modeled as separate groups. The introduction of mixtures into statistical models allows us freedom from this restrictive assumption because it does not require a priori knowledge of the embedded subpopulations.

Finally, the term "modeling" bears mentioning. At its most abstract, a model is simply a representation of reality. In a statistical discussion, "modeling" implies a mathematical representation, which is specified in a way that describes a *conceptual* model, which in turn describes the researcher's understanding of how the elements under study are interrelated. The model fit is determined by assessing the degree to which the relationships implied in the mathematical model recapture the information contained in individuals' experiences as they are represented in their given responses.

Combining the four terms into the phrase "latent variable mixture modeling" invokes the notion that, through mathematical representation, we can infer the presence of hidden subpopulations from the ways in which elements of a conceptual model are differentially interrelated. Indeed, this is precisely what the modeling approach is designed to do. In the following sections, we will explain in conceptual terms how the models work and give two illustrative examples of the application of this modeling approach to real data. First, however, we will provide a brief review of the emergence of this approach.

Historical Roots of LVMM

The mathematical representation from which latent variable mixture modeling derives is a pioneering fusion of two independent approaches to statistical modeling: structural equation modeling and finite mixture modeling. These two approaches were adopted by different fields of inquiry; structural equation modeling (stemming from the discipline of psychometrics) became the golden child of the social sciences and finite mixture modeling (arising from the discipline of statistics) was used more commonly in the physical sciences. The two statistical tools were

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used in very different ways in these two disciplines. On one hand, structural equation modeling seeks to reflect theoretical postulations about causes and consequences of human experience, testing hypotheses about effects – particularly direct, mediating (e.g., process), and moderating (e.g., intervention) effects – often in the context of an interdependent system of intrapersonal and socio-contextual elements. On the other hand, finite mixture modeling was used in the physical sciences to describe the shape of distributions that did not conform to the "ideal" of a bell-shaped curve (e.g., body weight distributions in which there is an overrepresentation of obese and overweight individuals as compared to underweight individuals). While early applications of this modeling approach were substantively atheoretical (e.g., Everitt & Hand, 1981), more recent applications draw substantive conclusions about the component mixtures in models similar to traditional cluster analysis (e.g., McLachlan & Peel, 2000)

Because a fuller understanding of these two disparate modeling approaches will facilitate comprehension of the complementary nature of the pair as they are combined in LVMM, we will describe the two component approaches in more detail. First, we will describe the modeling paradigm that underlies structural equation modeling. Then, we will describe the modeling paradigm underlying finite mixture modeling. Finally, the evolution of the LVMM approach from its precursors is described.

Structural equation modeling. Structural equation modeling (SEM; alternately known as covariance structure modeling) allows the researcher to specify and simultaneously estimate relationships among multiple constructs, using a system of linked equations (Browne & Arminger, 1995). As part of the system of equations, there is generally a measurement model (similar to factor analysis) and a structural model (similar to regression analysis). In the measurement model, sets of like items thought to measure the same construct are "mapped onto" an implied (latent) variable, or factor. The strength of the measurement model can be seen in the "ties" between the items and the underlying factor (i.e., the factor loadings) and in the amount of variability in the original items that remains unexplained by the latent factor (i.e., the residuals). The structural model, in contrast, provides information regarding the degree of association among different concepts that are represented by different latent factors in the model. These can be modeled statistically as regression effects, correlation effects, or a combination of the two for different relations throughout the modeled system.

In both the measurement and structural parts of the structural equation model, the researcher can place constraints on the structure the system takes. In other words, she can specify that two or more effects be estimated at the same value and she can specify the exact value of individual effects. This flexibility in modeling lends itself well to the kinds of research questions and hypotheses social scientists pose, such as whether or not there are gender differences in a phenomenon or whether there is an observable effect of an intervention program. Further, regression equations can be linked to form path models, the basis for testing hypotheses regarding the mechanisms by which a cause and effect relationship occurs.

Finite mixture modeling. The second statistical framework, finite mixture modeling, was developed to model phenomena that do not conform to the standard of a normal distribution, a common statistical assumption (McLachlan & Peel, 2000). Knowing the shape of the frequency distribution of a given construct in the population allows us to make assumptions about how values of this variable can be mathematically modeled as a function of another variable. When we encounter a decidedly non-normally distributed variable, standard parametric statistical modeling techniques are no longer adequate. However, when a non-normal distribution can be redescribed as being comprised of a mixture of a family of overlapping normal distributions (e.g., a small distribution at one extreme, followed by a slightly larger one, and another slightly larger one, as the values on the continuum increase), then traditional statistical techniques can be applied to these component normal distributions to describe relationships between non-normal variables. The trick, then, is to find the minimal number of normal distributions that underlie the non-normal distribution and specify the nature of these component distributions, as the components are not previously known. Through an iterative process – a process by which an initial solution is tried, compared to the observed data to determine the degree of misfit, adjusted, reapplied to the data, and so on – a best-fitting solution is found.

Latent variable mixture modeling: A hybrid. It was not until the late 1980s that the two approaches to statistical modeling were merged into a new class of models, latent variable mixture models (Muthén, 1989). In these models, inconsistencies in the way multiple variables map onto one another (i.e., non-normality in the multivariate distribution) give clues as to the presence of underlying mixtures of heterogeneous subpopulations. Because the LVMM approach is more general than the two constituent approaches, these models can reveal diversity in a complex system of relationships, as well as in a single relationship or even, as in traditional finite mixture modeling, in a single variable. Of key importance to the field of feminist research is that these new models allow us to detect multiple subpopulations (called "latent classes" in the statistical jargon), each with a different experiential story to tell, in our quantitative analysis and estimate the likelihood that a given individual belongs to each subpopulation.

In contrast to many other research methods used in feminist inquiry, the LVMM approach requires large samples. How large a sample must be will vary from application to application, depending on the number of latent classes indicated by the data and the prevalence of membership within each class, as well as the size of the differences in effects between classes (Lubke & Muthén, 2004). Generally it is a good idea to aim for at least 100 participants in each latent class; results from latent classes with fewer members should be interpreted cautiously.

Illustrative Examples

In this paper, we give two illustrative examples of such ground-breaking models and suggest the utility of this approach for other applications in feminist research. The data we use are drawn from the National Longitudinal Study of Adolescent Health (Add Health)[1].

Add Health is a longitudinal study of the behaviors of adolescents (in grades 7 through 12) and outcomes in young adulthood (ages 18 to 26). This nationally representative, school-based study considers the ways context plays a part in adolescents' lives by exploring the ways peers, schools, families, and communities may influence the health-related choices adolescents make. The study collected questionnaires from 90,118 adolescents, then followed a random subset of these adolescents with in-home interviews through three waves of data collection.

The first of our examples illustrates how LVMM can be used to explore measurement hetero-

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geneity (i.e., differences across individuals in the ways constructs are operationalized). For this example, we draw from the Add Health's battery of items from the Bem Sex-Role inventory (Bem, 1974, 1981). The second example—illustrating the use of LVMM in discovering individual differences in how constructs are interrelated (i.e., structural heterogeneity)—draws from items on the Add Health survey assessing daily activities in adolescence and from items assessing sexual practices in young adulthood. These models were fit using the statistical software program Mplus, version 3 (MuthÈn & MuthÈn, 1998-2004).

Measurement Heterogeneity. The Bem Sex-Role Inventory (BSRI: Bem, 1974, 1981) has been in wide use since the late 1970s (Choi & Fuqua, 2003). This assessment tool provides the research participant with a number of statements such as "I am compassionate" and "I am sensitive to the needs of others" to represent personality traits thought to be stereotypically "feminine," and "I am independent" and "I am dominant" to represent traits stereotypically "masculine". The participant is asked to rate herself/himself on a 7-point scale, from 1="never or almost never true" to 7="always or almost always true". The BSRI has been criticized for reifying socially constructed notions of gender role traits and the two factors have often been referred to as "instrumentality" and "expressiveness" instead of "masculinity" and "femininity" (e.g., Baucom & Sanders, 1978; Spence, 1984; Spence & Buckner, 2000; Spence & Helmreich, 1980).

We were interested in empirically verifying the universality of the factor structure of this assessment tool. While assessments of the factor structure of the BSRI have been conducted repeatedly over the 3 decades of its use (e.g., Blanchard-Fields, Suhrer-Roussel, & Hertzog, 1994; Choi & Fuqua, 2003), this new approach allows us to ask new questions regarding the factor structure: "Does the BSRI measure the same "masculinity" and "femininity" constructs for all the participants in the study?" and "If not, how many different conceptual formulations can be found in our data, how common are these conceptualizations, and how do they differ from one another?"

Our example, conducted for illustrative purposes only, draws from data submitted by 2,445 young women who were selected as part of the Couples Subsample of the Add Health Study design and who completed the short form of the Bem Sex-Role Inventory. The short form is comprised of a set of 20 items: 10 reflecting "masculinity" and 10 reflecting "femininity". A traditional confirmatory factor analysis conducted with these data shows an unusually strong factor structure (factor loadings 0.92 to 0.99 for masculinity; 0.97 to 0.99 for femininity). In practice, it is common to find factor loadings in the 0.60 to 0.80 range, whereas these factor loadings represent a concordance of items with the latent factors that is nearly perfect, signifying a *very* precise measurement of the underlying construct.

A reanalysis using the LVMM approach tells a very different story. We specified a series of latent class models, allowing measurement parameters to vary across latent classes. We found that a three latent class model best describes the data. Results of this model show two of these latent classes are sizable (47% & 46% of the sample), while a third represents only 7% of the total sample. While the latter latent class represents a very small minority, the model estimates are based on 165 individuals, affording enough stability of the factor structure for interpretation.

The pattern of the factor loadings shows that only the smallest latent class (Class #1) mimics the factor structure found in the traditional factor analysis (Table 1). The remaining two latent classes reveal very different structures. In one of these latent classes (Class #2), the factor structure for the femininity items is generally strong but the factor structure for the masculinity items is only marginal, with 3 items in the masculinity item set returning factor loadings below the customary 0.40 cutoff for interpretability (Gorsuch, 1983). In the remaining latent class (Class #3), the factor structures of both scales are notably weak, with 6 of the 10 masculinity items and 4 of the 10 femininity items below the interpretability cutoff.

These findings suggest that only for a tiny minority of the young women were the constructs of femininity and masculinity well measured by the BSRI. In about half of the sample, only femininity could be described adequately, albeit not perfectly, with a single latent construct. In the majority of cases, individuals' self-ratings of stereotypically masculine traits did not share a common underlying factor at all; rather, these women rated themselves according to these traits by invoking a multiplicity of personality dimensions in their ratings rather than a single one. Given these findings, it appears that a very extreme minority of individuals may drive the gender role stereotypes that continue in the popular and academic literatures and that, for many young women, the reality underlying gender roles may be more complex and multifaceted and not well described by the traditional BSRI factors. However, these results may also reflect empirical artifacts due to the skewed distribution of the underlying gender role constructs themselves, since these findings were conducted with an all female sample. The addition of male respondents to our analysis sample would provide greater variability in the gender role constructs as well as provide the opportunity to examine differences and similarities in men and women in gender role construction, and precursors and consequences of specific formations of gender. We intend to pursue this study further, using the LVMM approach to address these research questions.

This example shows how untested assumptions about the comparability of measurement across groups for which membership is not directly known can obscure researchers' understandings of key study constructs which can have profound effects on research findings as well as on policies based on these findings. Violations of this assumption can have profound effects on research findings, on policies based on these findings, and ultimately on the lives of individuals whose construction of these constructs is not adequately represented.

Structural Heterogeneity. Our second example, one that highlights the application of LVMM to detect heterogeneity in structural relations in the model, derives from the first author's previous work with her colleague, Sumru Erkut (Tracy & Erkut, 2004).[2] For this example, we were interested in testing the hypothesis that physical activity in adolescence protects girls from engaging in sexual practices that have higher physical and socio-emotional health risks as they enter adulthood. The impetus for this study comes from recent findings that participation in sports is concurrently associated with lower risky sexual behaviors among adolescent girls but not boys (Erkut & Tracy, 2000; Miller, et al., 1998; Sabo, et al., 1998).

Our analysis models were fit to data from a sample of young women (ages 18-26 at Wave 3: 2001-2002) who reported no significant disabilities at any of the three waves of assessment (n=3,905). Based on the frequency of engaging in various daily activities, such as walking, jogging, rollerblading, or participating in organized sports, we constructed a physical activity variable. The sexual risk indicators, obtained from the young adult assessment, include participants' reports of

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the lifetime number of sexual partners, the number of sexual partners within the previous year, reports of either having given or received sex for money or having had sexual intercourse with a known intravenous drug user, the number of unintended pregnancies, and whether or not she had ever been diagnosed or tested positive for sexually transmitted infections.

Initial models, using a traditional structural equation modeling approach to regress the sexual outcome variables on earlier physical activity and a host of covariates, did not support our hypothesis – none of the individual hypothesized effects were evident. Then, we tried a LVMM approach, allowing the effect of physical activity to predict latent class membership and individual sexual risk outcomes within each latent class. We found that two latent classes best describe the data: the first comprising about 52% of the sample and the second about 48%. In the first latent class, the indicators for sexual risk have low values (lifetime number of sexual partners = 2.23; probability of having had multiple sexual partners in the previous year = 0.00; probability of having had an unintended pregnancy = 0.10; probability of having had an STI = 0.07; probability of having had paid sex or sex with IV drug user = 0.00), representing low overall propensity for sexual risk in young adulthood. In the second latent class, a much higher sexual risk is evident (lifetime number of sexual partners = 4.36; probability of having had multiple sexual partners in the previous year = 0.51; probability of having had an unintended pregnancy = 0.28; probability of having had an STI = 0.27; probability of having had paid sex or sex with IV drug user = 0.05).

Results of this model show that adolescent physical activity significantly predicts lower probabilities of belonging to the Elevated Sexual Risk class (B=-2.00, SE_B=0.62, p<0.01). Thus, while the average sedentary adolescent girl has almost a 50% chance of belonging to the Elevated Sexual Risk class by early adulthood (see Figure 1), this vulnerability decreases with higher levels of physical activity until, at the highest levels of activity[3], the chance of belonging to the Elevated Sexual Risk class is only about 15%. The results of this model also show that, beyond the protective effect of physical activity on overall sexual risk, there is an additional protective effect among girls *within* the Elevated Sexual Risk class on sexual behaviors (i.e., prostitution and/or sex with an IV drug user) associated with profound health risks (B= -6.24, SE_B= 1.98, p< 0.01). This means that girls who are at least marginally physically active in high school are less likely than their sedentary counterparts to engage in these highly risky behaviors, even if they end up in the higher overall sexual risk class (see Figure 2). In the Lower Sexual Risk Class, there is essentially a zero probability of engaging in such risky sexual behaviors at any level of physical activity.

On the other hand, adolescent physical activity was found to be associated with a *greater* accumulated number of sexual partners within the Lower Sexual Risk class (B= 1.21, SE_B= 0.45, p< 0.01). This represents an increase from an average of about 2 sexual partners by young adulthood for young women who had been sedentary as adolescents to an average of about 3 sexual partners for those most active in high school (see Figure 3). As a comparison, young women in the Elevated Sexual Risk class reported an average of about 4 sexual partners with no appreciable differences by adolescent physical activity level (B= -0.48, SE_B= 0.45, *ns*).

While this finding may appear counterintuitive, examination of the predicted probabilities reveals that even the highest levels of risk in the Lower Sexual Risk class (i.e., those associated with sedentary girls) do not reach the lowest levels of risk in the Elevated Sexual Risk class (i.e., those associated with physically active girls). Indeed, if one considers the accumulation of sexual partners by young adulthood to have a developmentally normative level, physical activity in adolescence may serve to "normalize" otherwise unusually low levels of sexual experience. Taken in the context of the other sexual risk indicators, we can infer that physically active adolescent girls tend to make healthier choices regarding sexual risk behavior, even within the context of developmentally normative sexual activity. This finding suggests that the protective effect of being physically active as a teen may help to bolster good decision-making skills that will serve girls well as they negotiate sexual encounters throughout their early adulthood years.

This example shows how a potentially important and intervenable factor in preventing sexual risk outcomes, adolescent physical activity, may have been disregarded had we used traditional models of effect. The results of our reanalysis suggest that physical activity may indeed protect girls from later sexual risk, overall, and may also have differential effects on two particular outcomes (very high risk sexual behaviors and lifetime number of partners), based on the subpopulation to which she belongs. Further analyses could reveal early predictors of sexual risk vulnerability that could guide the selection of target populations for intervention efforts.

Discussion

This paper has introduced a new modeling technique that is particularly well-suited for use in feminist research efforts. With this modeling approach, multiple experiences can be detected, described, enumerated, and related to hypothesized predictors, antecedents, and descriptors. This is especially beneficial for feminist research: individuals need not be preassigned to groups based solely on social address *proxies* of power and privilege (e.g., gender, race/ethnicity, social class, etc). Instead, experiential disparities, *within* as well as *across* traditionally studied demographic groups can be examined. In this way, individual differences in experience are preserved while shared effects of social context are simultaneously acknowledged. A powerful application of this new modeling approach would be to reanalyze existing data in order to critically evaluate research that has produced "truisms" about gender, racial/ethnic, or social class differences, bringing back into the discourse the ways in which experiences can be similar as well as different for individuals in various social contexts.

This new approach to model testing has direct policy implications. Results from these types of analyses can generate more precise information for pinpointing those subpopulations for which the model guiding an intervention is likely to be applicable and subpopulations for which another model is more appropriate. It also has very straightforward implications for the study of unusual vulnerability in an otherwise relatively protected group or unusual resiliency in an otherwise risk-prone group, providing fertile ground for the generation of hypotheses regarding effective intervention efforts. Finally, because it arises from large-sample quantitative data, findings are more likely to be convincing to policy-makers, providing the potential for wide-scale influence of feminist research (Spalter-Roth & Harmann, 1991).

Conclusion

We recommend latent variable mixture modeling as a feminist approach to quantitative data analysis. It provides the power of statistical analysis required for policy change, while offering the ability to model the very kinds of differences that feminists have sought to explore and

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represent in qualitative research studies. With this method, though quantitative, participants are neither marginalized nor forced to have a "common identity" and qualitatively diverse subpopulations can be explored and studied in great depth.

And yet, while this approach goes a long way toward integrating the concept of "voice" into quantitative data analysis, the stories that are heard are necessarily limited to the system of constructs and interrelationships specified by the researcher. As in all studies, the richness of the results is limited to the type of information collected and included in the analysis model. For this reason, it is still vitally necessary to attend carefully to the stories of individuals, in their own words, and as they are offered in a less structured context. Interviews and/or focus groups provide invaluable richness on which to base decisions regarding sampling, measurement, design, and analysis. Follow-up interviews of representative individuals (for example, with those who are typical of each class, and/or atypical of the model) are also recommended in order to validate and more deeply understand the processes suggested by the relationships obtained in the analysis models as they resonate with the lived experiences of individuals for whom the results will be generalized.

At the same time, we also firmly believe that there is a value to qualitative methods beyond simply providing support for quantitative studies. Qualitative research, perhaps because it relies so heavily on a participant's own words and perspectives, often allows different pictures of human experience to emerge than does quantitative research that relies, for example, on numerical survey responses, scales, measurements, or close-ended questions.

Research design issues address the importance of "matching" research questions, the data collected, and the method of analysis and thus, the question often becomes: "What kinds of questions do we want to answer?" For example, although they clearly work well together, research offering an understanding of the factors involved in accurately predicting time to disclosure for children who are sexually abused (Goodman-Brown, Edelstein, Goodman, Jones, & Gordan, 2003) is not necessarily of greater value than research illuminating the way children sound (the words, tones, and metaphors they use) once they *do* they attempt to tell (Sorsoli, Kia-Keating, & Grossman, under review).

While latent variable mixture modeling can in no way take the place of qualitative research, it does allow us to examine, quantitatively, certain elements of experience that previously tended to be analyzed only within a qualitative paradigm. As Merecek (2003) wrote, "Many psychologists swim in the waters of logical positivism, empiricism, realism, and quantification without knowing they are wet" (p. 51). As feminists, we are well aware of these waters and acknowledge that both qualitative and quantitative methods offer possibilities and limitations. Latent variable mixture modeling can be a powerful tool that will allow us to "talk back" to prior research and offer innovative ways to understand human experience from a feminist perspective (DeVault, 1996). By shifting the focus of a quantitative analysis from descriptions of the potentially mythical "average" experience to the expectation that experiences differ and that these differences will be reflected in the data and are important to analyze, this new brand of empirical feminist research—just like other feminist approaches—will embrace a diversity of responses and honor the complexity of human experience.

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Table 1. Standardized factor loadings for BSRI factor mixture model.

	Class #1 n=165 (7%)	Class #2 n=1,129 (46%)	Class #3 n=1,151 (47%)
Femininity Items			
I am affectionate.	**0.72**	**0.52**	0.32
I am sympathetic.	**0.67**	**0.68**	0.39
I am sensitive to the needs of others.	**0.81**	**0.67**	**0.44**
I am understanding.	**0.67**	**0.72**	**0.41**
I am compassionate.	**0.91**	**0.72**	**0.49**
I am eager to soothe hurt feelings.	**0.82**	**0.63**	0.39
I am warm.	**0.93**	**0.77**	**0.60**
I am tender.	**0.92**	**0.78**	**0.71**
I love children.	**0.80**	**0.46**	0.22
I am gentle.	**0.90**	**0.75**	**0.67**
Masculinity Items			
I defend my own beliefs.	**0.46**	0.24	0.03
I am independent.	**0.76**	0.27	0.12
I am assertive.	**0.64**	**0.53**	**0.40**
I have a strong personality.	**0.89**	**0.67**	0.12
I am forceful.	**0.49**	**0.46**	**0.63**
I have leadership abilities.	**0.93**	**0.42**	0.29
I am willing to take risks.	**0.65**	0.36	0.38
I am dominant.	**0.76**	**0.63**	**0.72**
I am willing to take a stand.	**0.84**	**0.57**	0.33
I am aggressive.	**0.61**	**0.60**	**0.72**

Note: Interpretable factor loadings are bolded.

Figure 1. Probability of belonging to the Elevated Sexual Risk Class by young adulthood, by level of physical activity in adolescence.

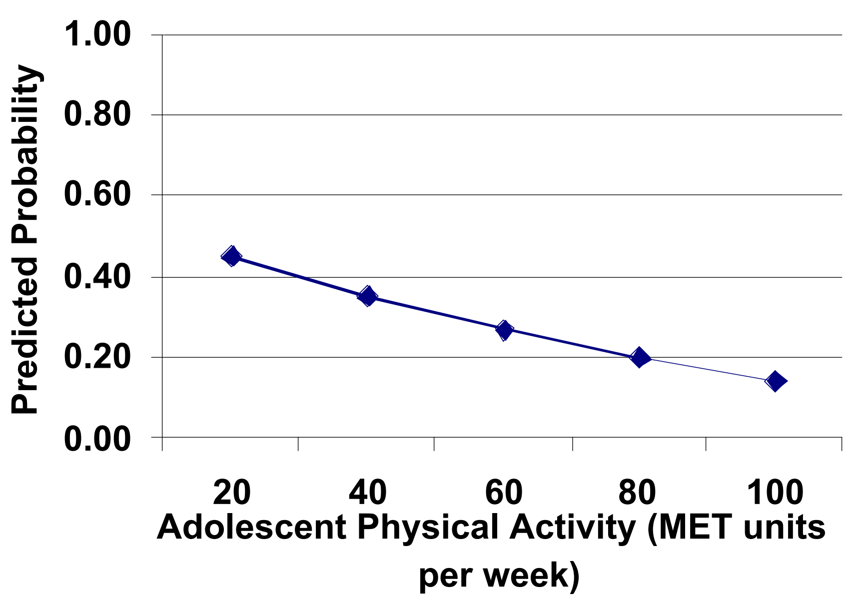


Figure 2. Probability of engaging in very risky sex in young adulthood, by level of adolescent physical activity for those in the Elevated Sexual Risk Class.

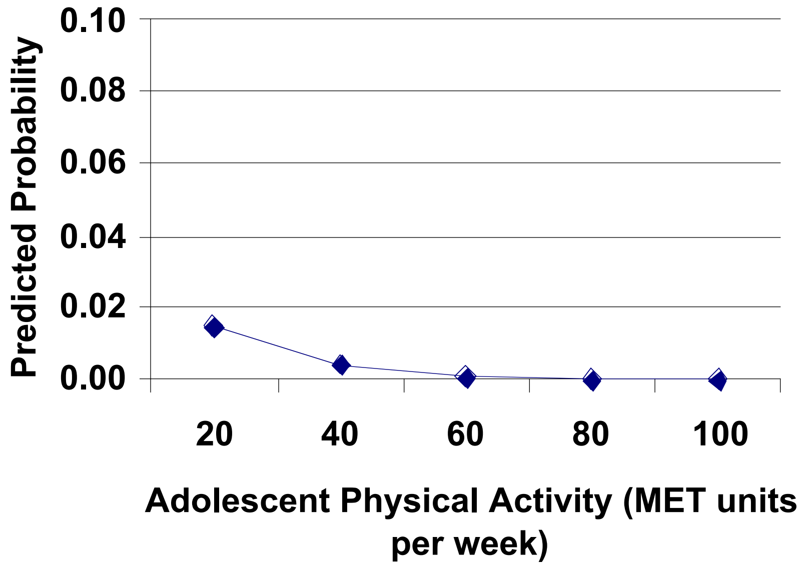
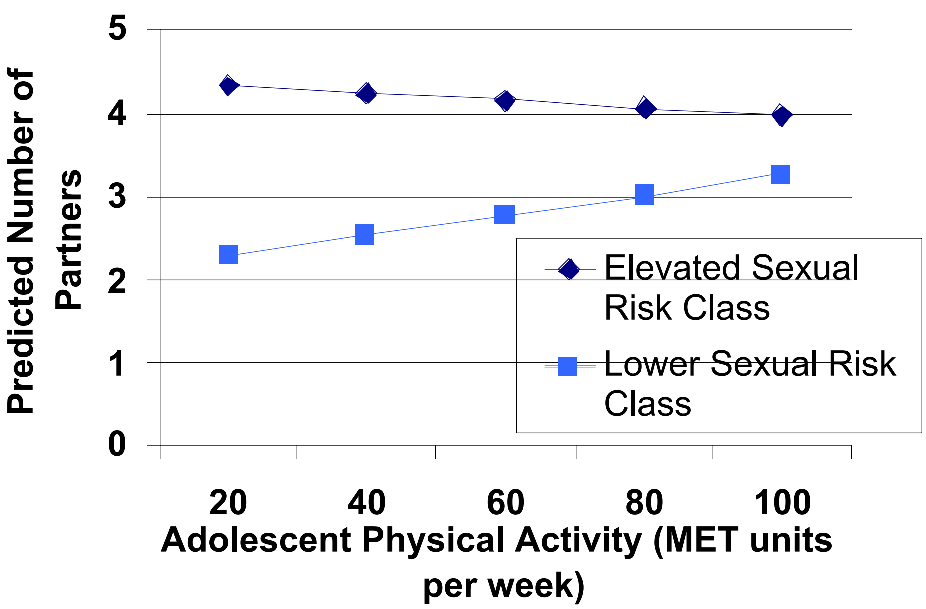


Figure 3. Accumulated number of sexual partners by young adulthood, by level of adolescent physical activity and sexual risk class.



(Footnotes)

[1] The Add Health project [J. R. Udry (PI) & P. Bearman] was funded by an NICHD grant (P01-HD31921) to the Carolina Population Center, University of North Carolina at Chapel Hill, with cooperative funding from 17 other agencies. Data files can be obtained by contacting the Carolina Population Center, 123 West Franklin Street, Chapel Hill, NC 27516-2524 or visiting by the website *http://www.cpc.unc.edu/addhealth.*

[2] This research was funded by a grant (1 R01 HD38530-01A1) from the National Institute for Research in Child Health and Development.

[3] As a comparison, a minimum of 50 METs per week are recommended by the CDC.