Latent Class Analysis and Latent Profile Analysis

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Latent class analysis (LCA) and latent profile analysis (LPA) are powerful techniques that enable researchers to glean insights into "hidden" psychological experiences to create typologies and profiles to provide better-informed community-based policies and practice. These analytic methods have been used in a variety of domains, such as: psychosis symptomatology in the general population (Kibowski & Williams, 2012; Murphy, Shevlin, & Adamson, 2007; Shevlin, Murphy, Dorahy, & Adamson, 2007); substance abuse (Cleveland, Collins, Lanza, Greenberg, & Feinberg, 2010; James, McField, & Montgomery, 2013), peer victimization (Nylund, Bellmore, Nishina, & Graham, 2007), and anti-social/self-defeating behavior (Rosato & Baer, 2010). LCA and LPA are versatile methods of dealing with data of interest to community-based researchers in a deep and psychologically grounded way. This chapter will address the nuances of how and when to use LCA and LPA. Case studies of LCA and LPA will also be presented to illustrate the applicability of these techniques.

Introduction to Latent Class Analysis

The main aim of LCA is to split data that are apparently homogeneous overall into sub-classes of two or more different homogeneous groups or classes. Study participant responses to a questionnaire, structured interview, or behavioral checklist would be used as the basis for making probabilistic assessments of the likelihood of each participant being assigned to one of these classes. A participant's likelihood of belonging to any of the other latent classes would also be calculated, and then decisions would be made as to the ultimate class membership that each respondent would assume. The beneficial role that LCA can have is that, once class membership has been assigned to each participant in relation to the pattern of responses or behaviors, this class membership can be used to inform policies and practice-based interventions aimed at targeting a specific latent class that has emerged from the analysis. An example of the potential for this method can be seen in a study of the transportation-related attitudes and experiences of workers (Williams, Murphy, & Hill, 2008). In this study, latent class analysis was deployed to examine the role of multimodality (i.e. using more than one mode of transportation) versus single transport mode use on commuters' psychological well-being.

Other community-level analyses have utilized LCA to investigate how to encourage sections of the population to engage more in community-based arts activities (Biggins, Cottee, & Williams, 2012). LCA is also helpful for testing population-wide phenomena and epidemiological trends, such as the potential existence of psychosis symptom experiences being measured along a continuum throughout the general population (e.g. Murphy et al., 2007; Shevlin et al., 2007), rather than as a dichotomous, psychiatrically driven and rare phenomenon.

LCA is usually appropriate for samples of at least 100 participants, although there is evidence that Monte Carlo simulation could be used to model probable class solutions with data sets of smaller size and to thus extrapolate likely class numbers for hypothetical larger data sets (Nylund, Asparouhov, & Muthen, 2007). The method of LCA is grouped within the family of structural equation modeling (SEM) techniques, such as confirmatory factor analysis (CFA). In contrast to CFA, however, which could be construed to be primarily variable-centered, LCA is more of a person-centered approach because of its focus on participants' characteristics and on how a pattern of responding to questions can provide insight into different participant groups' experiences, behaviors, emotions and cognitions. However, although LCA and LPA could be termed to be largely person centered in orientation, it has been argued that person-centered and variable-centered methods are rarely independent of each other (Masyn, 2013).

LCA is exploratory in emphasis and concerns itself with unearthing heterogeneity from seemingly homogeneous samples. The drive to find this potential diversity also underpins why

LCA is more generically labeled as “mixture modeling,” as the analyst will use probabilistic techniques to draw inferences about the possible mix of subgroups within a population that can be ”unmixed.” This mixture can be explained by something the variables have in common or by something the subgroups of people have in common, or, alternatively, both persons and variables could share this commonality.

The Process of Undertaking an LCA

Extraction of homogeneous classes with LCA would adhere to the following process. Before conducting an LCA, the coding of the indicator variable data and the likely class type to be extracted should be borne in mind. Data coding is mainly categorical and often dichotomous, although LCA is sufficiently versatile to accommodate ordinal coding, (e.g. Cleveland, Collins, Lanza, Greenberg, & Feinberg, 2010; LaFramboise, Hoyt, Oliver, & Whitbeck, 2006). Dichotomous coding could reveal the presence or absence of: an occurrence (e.g., a traumatic event), a psychological phenomenon (e.g., a symptom of ill health, such as hallucinations), or a diagnosis (e.g., classing someone as having obsessive-compulsive disorder); the coding could encompass a feeling, either as a dichotomously (e.g. ”satisfied” versus ”unsatisfied”) or differently (e.g., “never”,”sometimes” and ”often”) scaled state. With LCA, the process is mainly exploratory, and, although the indicator variables could be coded as categorical or ordinal, the resultant latent classes will always be categorical. Although some studies seem to demonstrate the presence of latent classes that may be scale-like as if on a continuum (e.g., Murphy et al., 2007; Shevlin et al., 2007), this appearance can be deceptive, as LCA is primarily involved in extracting classes that are essentially categorical.

To achieve the aim of establishing categorical latent classes, one can employ the Expectation Maximization algorithm, which utilizes the full information maximum likelihood method of class extraction (Masyn, 2013) by randomly allocating people into classes and estimating a one-class solution, a two-class solution, and so on, until inspection of a range of fit statistics demonstrates the presence of a best-fitting solution. Model fit is evaluated with the Likelihood Ratio chi-square (LRχ^2), Bayesian Information Criterion (BIC), Sample Size Adjusted BIC (SSABIC), Akaike Information Criterion (AIC), Consistent AIC (CAIC) and the Lo-Mendell-Rubin adjusted Likelihood Ratio Test (LMR-LRT). Of all of these fit statistics, the BIC has been identified as performing the most reliably, although the Bootstrapped Likelihood Ratio Test (BLRT) has also been commended (Nylund, Asparouhov, et al., 2007).

Evaluation of the class solutions takes place by appraising when the class solutions have the lowest BIC, SSABIC, AIC, and CAIC values. Lower LRχ^2 values are also desired, and ideally these should be associated with a nonsignificant test value, although this is often a rare finding because the chi-square statistic is adversely affected by larger samples (Bollen, 1989; Tanaka, 1987), with a higher risk of committing a Type I statistical error. By contrast, a statistically significant LMR-LRT value is indicative of better fit. With the BLRT, this statistic helps to evaluate whether a model improves significantly from the model with k – 1 classes, where k is the number of classes for each analysis and there is an assessment as to whether a more parsimonious fit is available (Asparouhov & Muthén, 2012; Dziak, Lanza, & Tan, 2014). The entropy value (i.e. ranging from 0 to 1) for each class solution could be used, with higher entropy values indicating better probabilities of being able to successfully classify participants into a latent class, depending on the number of latent classes being extracted (Masyn, 2013). Finally, the ultimate decision on the optimal number of classes to be extracted rests on whether the class solutions make sense through inspection of the posterior probabilities for class membership in relation to each indicator variable. Higher posterior probabilities for some indicator variables (e.g., 70% likelihood or higher of endorsing an item/behavior) may offer clues as to the probable label to be given to the class and the persons who belong in it. Very low probability of endorsing certain indicator variables may also provide insights into what the class could be called. The posterior probabilities can be mapped out as a graphical plot (see Figure 1), with the likelihood of endorsing an item ranging from 0% to 100% and being marked from 0.00 to 1.00 on the y-axis or in tabular form.

As can be seen in Figure 1 (adapted from Williams et al., 2008), some respondents in this United Kingdom-wide study of work-related travel had a 100% likelihood of endorsing the ”cycle” item and had a 10% chance of endorsing the ”train” item. Another class was labelled the ”rail” class, as there was a high chance of respondents endorsing the ”train” item and (relative to those in the other classes) a higher probability of endorsing the ”tram” or ”tube” (i.e. the London Underground). There was also a ”bus” class and a ”car” class that represented higher likelihood levels of endorsing items relating to these modes of transport. It should be noted that this analysis took into account multimodality by entertaining the possibility that commuters may use more than one method of travel to get to and from work. This study was able to uncover whether data obtained from commuters could be split into a two-class solution (e.g., public transport class versus private transport class) or other potential solutions. The study found four latent classes in relation to commuting behavior, and we were able to see how certain latent classes of commuting could be related to greater risk of commuting-related stress.

With a tabular example of posterior probabilities in Table 1, which has been adapted from Ronzio, Mitchell, and Wang’s (2011) study of witnessed community violence among African American mothers living in urban environments, we can see that a two-class solution was extracted from these 209 participants’ data: (a) a “higher witnessed community violence exposure” class and (b) a “lower witness community violence exposure” class. Table 1 demonstrates that women in a “higher witnessed community violence exposure” class had a relatively higher probability of hearing a gunshot “often” when compared with the “lower witnessed community violence” class. In fact, although the probabilities of hearing a gunshot “sometimes” was similar for both groups (i.e., 56% vs. 49%), the differences between the two classes in hearing a gunshot “never” or “often” were quite stark (12% vs. 51% and 31% vs. 0% respectively). This table also demonstrates the versatility of the LCA method in being able to accommodate differently coded indicator variables when comparing various categorical-type latent classes and the likely class membership in accordance with the probability of endorsing certain items at varying levels of agreement. The following section provides further insights into how to deploy LCA in community-based research, along with outlining the nuances involved in employing this method.

Case Study of LCA

An illustrative example of the potential for LCA in community-based research can be seen from the following study by the first author and his colleagues (Williams, Humberstone, & Harris, 2010) that was conducted with a sample of more than 4,000 participants drawn from one county in the East Midlands in England. This study was commissioned by the Derbyshire Arts Development Group and was aimed at inquiring into the reasons why some members of the general population did not engage with arts and cultural activities organized in the region. Respondents were asked about their participation in a number of arts and cultural activities and were also prompted to give reasons why they did not take part in these kinds of activities. The reasons for not taking part are depicted in Table 2.

After excluding "don't know" responses, there were 17 possible reasons that participants could choose. Respondents could endorse any (or none) of these reasons, so there were 2^{17} (i.e. 131,072) different response patterns that could be obtained (e.g., "yes" to all items was one possible response pattern; other permutations might be endorsing the first item out of the list of reasons and not endorsing any of the others). From this sample, 654 response patterns were elicited, but clearly we would not want to extract 654 different latent classes. A more parsimonious and manageable solution was needed. A six-class solution was chosen through inspection of the fit statistics (Table 3). This decision was attributed to the BIC value reaching its nadir at the six-class solution. The LMR-LRT also declined in value and was statistically significant up until the seven-class solution, which was when the value became nonsignificant (p = 0.15), which was interpreted as the six-class solution being markedly better than the seven-class solution. The entropy value for the six-class solution also showed that 71% of the sample could be accurately categorized on the basis of their class membership. Although the entropy value for the seven-class solution was also 0.71, we have already uncovered with the LMR-LRT statistic that this solution is not significantly better than the six-class solution. As a result of the profile of these fit statistics, the six-class solution was chosen to be the most accurate representation of how people were responding in relation to reasons given for not taking part in the arts.

The posterior probabilities could have been mapped out in a profile plot, but this may have been difficult to interpret from visual inspection of the probability of endorsing 17 items in relation to being a member of any one of six latent classes. Instead, we examined the table of conditional probabilities, and inferences were made about what would be appropriate labels for each latent class. Through this process, we were able to identify the classes, which included: an “arts resistant” class (i.e., high likelihood of endorsing “not really interested” and moderate levels of probability of endorsing “don’t really know enough about it”, “It’s difficult to find the time,” and “I wouldn’t enjoy it”) and an “uninformed” class (i.e., high probability of endorsing “not enough information on what is available” and moderate levels of likelihood of endorsing “not enough notice about the event”), to name but a few of the latent classes that could be unearthed. Overall, this approach proved advantageous in modeling the mentalities and behaviors of a population within a certain region. After interventions addressing these types of hidden barriers uncovered through LCA, a follow-up study could be carried out to examine whether the latent classes still existed in the general population within a region and the prevalence of such barriers to participation. Such a follow-up study was indeed conducted with another sample of 4,000 participants within the same locality (Biggins et al., 2012) and showed reductions in some of the barriers to participation latent classes, such as the prevalence of an “isolated” class of respondents declining from 17.7% of the sample in 2008 to 5.0% in 2011. Clearly, LCA has the capacity to see if a typology of phenomena, such as barriers to arts participation, can exist over time when assessing data from two time points with two different samples studied with a cross-sectional design.

Introduction to Latent Profile Analysis

LPA can also offer something new and useful to a community-based researcher. Community-based studies employing LPA have, for example, analyzed coping among ethnic minority youth (Aldridge & Roesch, 2008) and profiles of urban-based African American adolescents (Copeland-Linder, Lambert, & Ialongo, 2010) involving combinations of the three variables of violence exposure, parental monitoring, and parental involvement. The latter study examined how their obtained profiles differentially predicted depressive symptoms and aggressive behavior. Specifically, Copeland-Linder et al. (2010) were able to compile three class profiles (a “vulnerable” class, a “moderate risk/medium protection” class, and a “moderate risk/high protection” class), which could aid in the development of targeting at-risk youth and creating programs to help young people’s well-being levels when violence in the community is salient and/or frequent.

Overall, LCA and LPA are two kinds of person-centred mixture modeling analyses that are used to identify subgroups of an underlying categorical latent variable with data obtained from cross-sectional designs. As such, the two types of analyses are very similar, and fit statistics that are scrutinized in LCA are also used in LPA. Rather than repeat for the reader what these statistics entail, we would note that the main difference between LCA and LPA is in the type of indicator variables used. While LCA is often undertaken on categorical indicator variables, LPA is used for continuous indicator variables.

In turn, there are some differences between LCA and LPA in the nuances of the analyses undertaken. In LCA, the shapes of the latent classes are defined by the assumption of local independence (i.e., the indicator variables are independent of each other within the latent classes), and the latent classes are described by the differing posterior probabilities (i.e., specified after the class solution has been extracted) of endorsing each indicator variable based on class membership. In contrast, the shape of the latent classes in LPA is not specified by the assumption of local independence, and the resultant best-fitting LPA solution is described by the different mean scores on each indicator variable, depending on class membership. With respect to the specification of what the latent classes are shaped like in LPA, Masyn (2013) suggested that four different specifications should be tested alongside the best-fitting solution. The first, most restrictive, specification describes a model in which the shapes of the resultant classes are constrained to be the same (i.e., variances and covariances are restricted to be the same across classes) and the assumption of local independence is implemented (i.e., the indicator variables are not allowed to covary within a class). The second and third specifications relax either one of these restrictions (i.e., local independence is assumed or not, and variances and covariances are restricted to be the same across classes, or not, respectively). The fourth, and final, specification relaxes both of these constraints;the variances and covariances are not restricted to be the same across classes (i.e., differing shapes across the classes), and the error variances of the indicator variables are allowed to covary (i.e., no local independence is assumed). Masyn (2013) suggested that these four specifications should be assessed alongside the different number of classes to arrive at a best-fitting solution of the LPA that takes into account both the best-fitting shape and best-fitting number of classes.

This best-fitting solution in LPA is described by the different mean scores on each indicator variable, depending on class membership. Figure 2 provides an example of how data from the National Comorbidity Survey of more than 8000 participants in the United States were analyzed with LPA to elicit five homogeneous groups that were then compared on three different behaviors labelled as psychopathological and operating on continuous dimensions of “externalizing”, “internalizing”, and “psychosis” type profiles (Fleming, Shevlin, Murphy, & Joseph, 2014).

Case Study of LPA

Geiser, Okun, and Grano (2014) provided an excellent applied example of LPA. They were interested in what motivates people to volunteer and provide unpaid services to the community at large. The study was specifically focused on how different forms of motivation (i.e., amotivation, extrinsic motivation, and intrinsic motivation) interact and predict frequency of volunteering.

Furthermore, differences in sex and nationality were examined in this cross-national study of American and Italian participants.

Mean scores for six items (i.e. amotivation, intrinsic motivation, and four items for varying degrees of autonomy in extrinsic motivation) were evaluated. In order to undertake the LPA, it was assumed that there would be local independence (i.e., no covariance between indicator variables within the identified latent classes) and equal variances and covariances across the identified latent classes (i.e., same shape across classes). This is just one of the four specifications for the shapes and sizes of the latent classes that Masyn (2013) had advised to explore when deciding on the best-fitting class solution. However, the researchers were interested in inspecting the latent profile solutions for each of the two nationalities (American vs. Italian) and their respective sex (female vs. male). It would have added far too much complexity to take these four models (nationality paired with sex) and test each of them for the best-fitting shape and best fitting class solution to test four specifications (i.e., local independence, or not, paired with equal variances/covariances, or not) for each number of classes examined. Checking a two-class through to a six-class solution would have meant 20 solutions (i.e., 5*4 specifications) solely based on the best-fitting shape and best-fitting class solution. These would then need to be checked for each model (nationality by sex), resulting in 80 solutions (i.e. 20*4 models).

Geiser et al. (2014) based their initial analyses on Nylund, Asparouhov, et al.'s (2007) recommendations that the BIC, SSABIC, BLRT and LMR-LRT should be compared for a one- through to a seven-class solution for the four different models (nationality by sex). Due to these fit statistics not providing a consistent result for the best-fitting solution, Geiser et al. (2014) followed Marsh, Lüdtke, Trautwein, and Morin's (2009) recommendation of ensuring that the best-fitting solution described not only quantitative changes but also qualitative changes between the classes. The researchers judged the six-class solution to be the most interpretable with both qualitative and quantitative changes for all four models. A further multigroup LPA was undertaken to test similarities of the class solutions for the four different models (nationality by sex). A six-class solution was decided upon for the four models (nationality by sex), in which each model had differing class sizes for these six classes. The frequency of actually volunteering was then added to the model, and the researchers' original hypothesis-that participants who scored highly on intrinsic motivation and high in extrinsic motivation would volunteer the most frequently-was supported.

Limitations of LCA and LPA

One of the main limitations of LCA and LPA is that the identified classes may not necessarily always (and without further validation) refer to existing subgroups within the population. Superfluous classes can be identified due to nonnormality of the data, nonlinear relationships between the indicator variables, or a misspecification of the model (Bauer & Curran, 2004). As both LCA and LPA are types of finite mixture modeling analyses, the assumption is that heterogeneous data can be explained by homogeneous subgroups that are mixed together. Thus, the nonnormality and nonlinearity that are observed in the heterogeneous data could be hypothesized as being attributed to the mixture of these subgroups that have been identified through the use of LPA and LCA. However, there are other possible explanations beyond the presence of latent classes as to why data may be distributed in a nonnormal and nonlinear fashion (Bauer & Curran, 2004). This may lead to the erroneous identification of classes that are meant to explain nonnormality or nonlinear relationships that are found within the data.

If the aim of community-based research that utilizes LCA or LPA is to make an explicit statement of having identified real subgroups in the population, then other possible explanations for nonnormality and nonlinearity of the data need to be investigated and potentially ruled out (Bauer & Curran, 2004). Simply deciding on a best-fitting solution by undertaking an LCA or LPA would not be sufficient to prove that these classes actually exist as tangible groups of people, so community-based researchers would still need to be cautious of reifying any classes that have been extracted.

Conclusion

LCA and LPA offer versatile solutions to community-based researchers for dealing with data obtained through cross-sectional designs, especially with large samples of data. These analytic methods can be powerful tools to guide theory generation and testing. Most importantly, LCA and LPA can inform the development of typologies of underlying behaviors, attitudes, and perceptions that may not be noticeable otherwise. These methodological approaches can help form the basis for informed decision making and the development of evidence- based policies, practices, and interventions aimed at improving people's quality of life and well-being.

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Table 1

Posterior Probabilities in Relation to Latent Class for Urban African American Mothers Who Had Witnessed Community Violence (WCV)

	Latent class	
Type of exposure	Higher WCV exposure	Lower WCV exposure
Heard a gunshot		
Never	0.12	0.51
Sometimes	0.56	0.49
Often	0.31	0.00
Saw an arrest		
Never	0.16	0.72
Sometimes	0.58	0.28
Often	0.26	0.00

Note. From "The Structure of Witnessed Community Violence Amongst Urban African American Mothers: Latent Class Analysis of a Community Sample," by C. R. Ronzio, S. J. Mitchell, and J. Wang, 2011, *Urban Studies Research*, p. 5. Reprinted with permission.

Table 2

Reasons Given for Not Attending Arts and Cultural Events

Item	Number (% of those who responded to item)
It’s difficult to find the time	1,494 (34.54%)
It costs too much	1,419 (32.80%)
Not enough information on what is available	1,123 (26.0%)
Not enough notice about the event	784 (18.1%)
It’s not close enough to where I live/work	687 (15.9%)
Not really interested	653 (15.1%)
Nothing stops me from attending arts and cultural events	617 (14.3%)
I don’t know enough about it	542 (12.5%)
Lack of transport	529 (12.2%)
Health isn’t good enough	367 (8.5%)
I don’t have anyone to go with	343 (7.9%)
Never occurred to me	185 (4.3%)
I might feel uncomfortable or out of place	171 (4.0%)
I wouldn’t enjoy it	147 (3.4%)
Other reasons	156 (3.6%)
Don’t know	77 (1.8%)
It is often too complex or confusing	63 (1.5%)
Against my religion/beliefs	25 (0.6%)

Table 3

Reasons Given for Nonparticipation in Arts and Cultural Activities–Fit Statistics for the Latent Class Analysis

Model	Log likelihood	Free parameters	LRχ2 (df) *p*	AIC	BIC	SSABIC	LMR-LRT (*p*)	Entropy
Two classes	-23177.58	39	3599.39 (262040) 1.00	46433.15	46681.67	46557.75	2111.90 (0.00)	0.64
Three classes	-22834.32	59	2942.01 (262023) 1.00	45786.64	46162.61	45975.13	682.44 (0.00)	0.63
Four classes	-22623.55	79	2538.01 (262005) 1.00	45405.09	45908.51	45657.48	419.04 (0.00)	0.70
Five classes	-22435.54	99	2432.92 (262003) 1.00	45069.09	45699.95	45385.37	373.20 (0.0461)	0.68
Six classes	-22283.91	119	2186.01 (261986) 1.00	44805.83	45564.14	45186.01	301.46 (0.0035)	0.71
Seven classes	-22201.58	139	2045.14 (261968) 1.00	44681.17	45566.93	45125.25	164.04 (0.1456)	0.71

Note. LRχ2 = likelihood ratio chi-square, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SSABIC = Sample Size Adjusted BIC, LMR-LRT = Lo-Mendell-Rubin Likelihood Ratio Test.

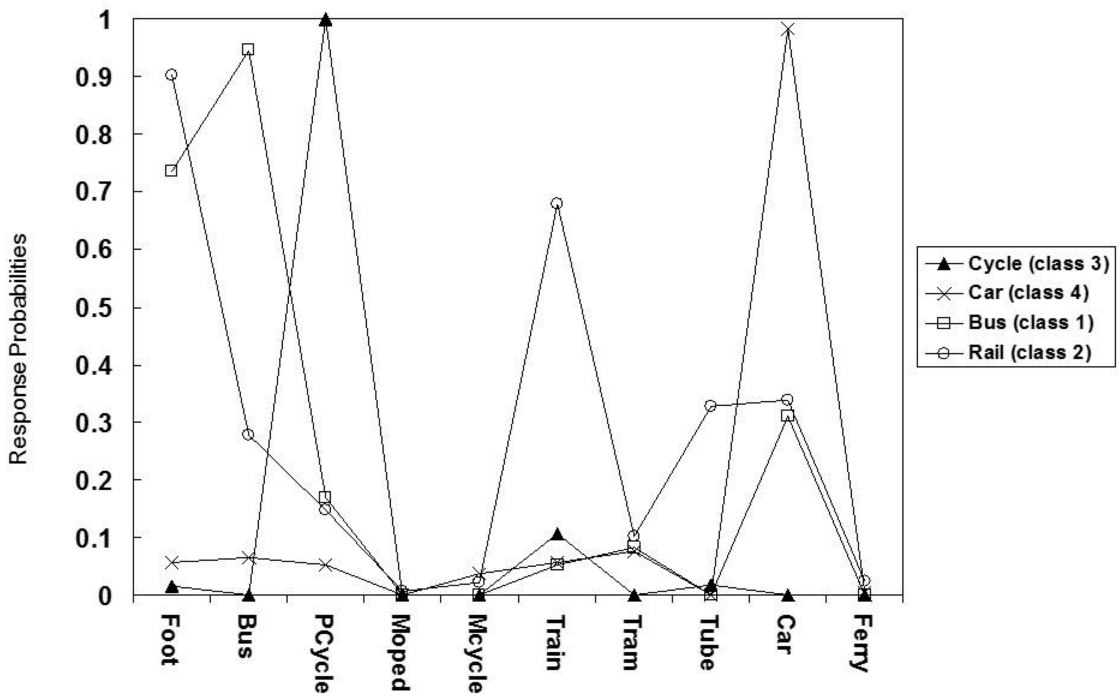
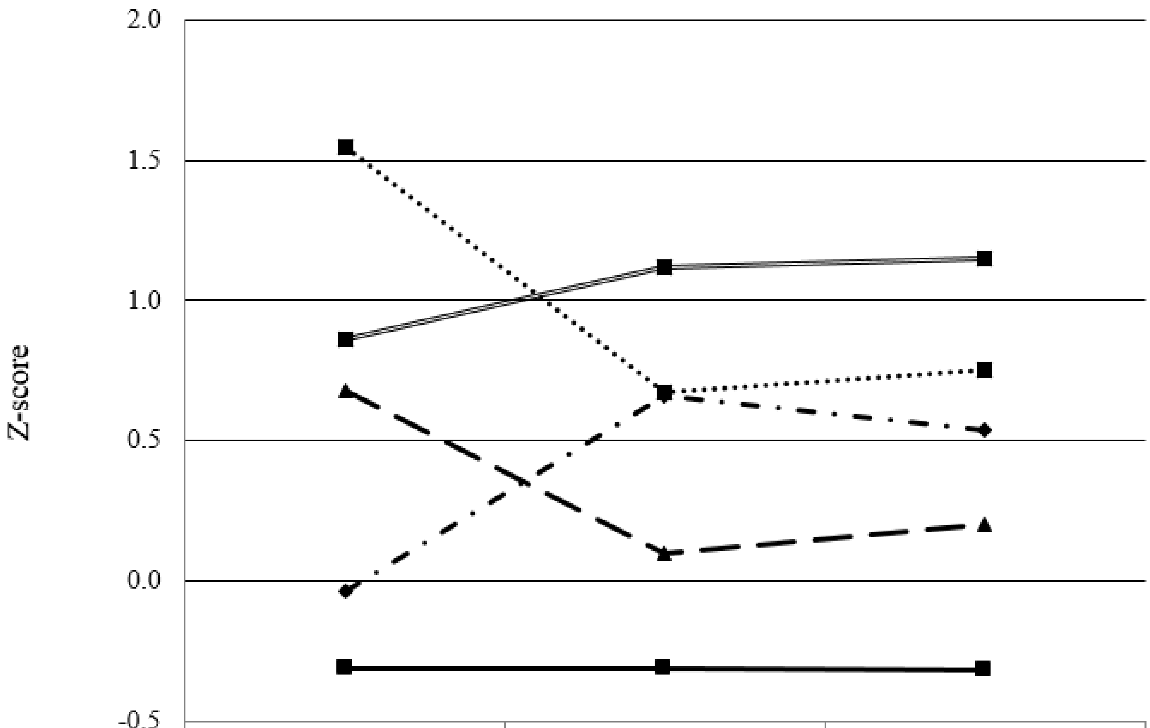


Figure 1. Probability of endorsing different commuting modes based on latent class membership.



	Externalizing	Internalizing	Psychosis
Series1	-0.04	0.66	0.54
Series2	-0.31	-0.31	-0.32
Series3	0.68	0.10	0.2
Series4	1.55	0.67	0.75
Series5	0.86	1.12	1.15

Figure 2. Latent profile plot of psychopathological profiles across dimensions. Adapted from "Psychosis Within Dimensional and Categorical Models of Mental Illness," by S. Fleming, M. Shevlin, J. Murphy, and S. Joseph, 2014, *Psychosis*, p .8. Reprinted with permission.