Journal of Cross-Cultural Psychology
2015, Vol. 46(1) 3–18

DOI: 10.1177/0022022114555764
jccp.sagepub.com
SAGE

A Typological and Probabilistic Approach for Exploring Cross-Cultural Differences: Two-Level Latent Class Models

Hsiu-Ting Yu[1]

Abstract

Discrete latent constructs are useful and versatile tools when applied to theories or hypotheses typically made in cultural psychology. The two-level latent class model (TL-LCM) is proposed as an analytical framework using discrete latent variables for underlying typological structure. The typological and probabilistic characteristics of the TL-LCM offer several advantages over the traditional dimensional and deterministic models commonly used in cross-cultural research. Specifically, the TL-LCM allows researchers to form alternative typological hypotheses about the latent constructs instead of being bound with dimensional assumptions of latent constructs. In addition, the TL-LCM provides a probabilistic approach to studying the latent structures simultaneously at two nested levels. The probabilistic characteristic of the TL-LCM also relaxes the strong and often unrealistic assumption that individuals within the same higher unit are homogeneous. Therefore, the TL-LCM not only offers researchers new potential perspectives in exploring differences between cultures, but it also facilitates the process of forming theories and hypotheses so that knowledge and understanding of cultural differences and similarities can be further advanced. Two examples demonstrated the usefulness and flexibility of applying the TL-LCM to analyze nested cross-cultural data. The examples showed that differences between countries can be thought of as arising from the fact that individuals within different countries have different probabilities of falling into one of multiple classes, rather than assuming that the individuals within each country are homogeneous.

Keywords

methodology, measurement/statistics, cultural psychology

Introduction

One goal of studies in cross-cultural psychology is to identify differences and similarities between cultural groups and between individuals belonging to different cultural groups (Fontaine, 2008). These data are complex because of the nested relationship between individuals and their cultural groups. Various statistical methods have been proposed for analyzing this type of nested data collected in cross-cultural studies. Standard statistical methods include correlation techniques,

[1]McGill University, Montreal, Québec, Canada

Corresponding Author:
Hsiu-Ting Yu, McGill University, Department of Psychology, 1205 Dr. Penfield Avenue, Montreal, Quebec, Canada H3A 1B1.
Email: ht.yu@mcgill.ca

regressions, ANOVAs, confirmative factor analysis (CFA), exploratory factor analysis (EFA), multidimensional scaling (MDS), principal component analysis (PCA), structural equation modeling (SEM), and multiple-group versions of CFA and SEM. In addition, latent variable modeling and multilevel modeling are the two main methodological techniques used for cross-cultural comparisons.

Latent variable modeling takes observed measurements and infers underlying structures (called latent variables) to represent unobserved psychological constructs of interests. Latent variables can be defined at either the group or the individual level. For example, Hofstede (1980) identified the four culture-level dimensions based on the cultural averages of work values: individualism–collectivism, masculinity–femininity, power distance, and uncertainty avoidance. In his model, these dimensions were only valid at the cultural level, not the individual level. Conversely, Triandis, Leung, Villareal, and Clark (1985) developed a scale to measure the individual-level counterpart of culture-level individualism–collectivism. To avoid confusion with the culture-level construct, they introduced the terms *idiocentrism* and *allocentrism* for the individual-level constructs.

Some constructs apply at both the cultural and individual levels, but at each level the construct may have similar or different components. For example, Schwartz (1992) proposed 10 distinct motivational values, and the contents and structure of these values are different at the individual and group levels. These examples suggest that latent variables can be used to jointly or separately represent hypothesized latent constructs at both cultural and individual levels. Researchers then can use these latent constructs to form hypotheses according to their theoretical assumptions and formally test these hypotheses with statistical methods.

Multilevel modeling is a popular technique developed to account for the dependencies between levels in nested data structures (Hox, 2002; Raudenbush & Bryk, 2002; Snijders & Bosker, 2012). This modeling approach has become a preferred analysis technique in studies of cross-cultural psychology (see, for example, Fischer, 2009; Fontaine, 2008; van de Vijver, van Hemert, & Poortinga, 2008) because the data collected in this field are usually nested. Individuals are nested within their country, and this nesting introduces dependencies, as individuals in the same group share something in common (e.g., attending the same school, living in the same neighborhood, or being educated in the same school system). And it is important that the dependencies due to nested data structure should be properly taken into account in the analysis.

One way to deal with the nested data structure is the multiple-group approach, in which each country is considered individually. For comparisons among a few countries, this approach is still manageable. However, as the number of countries increases, the multiple-group approach becomes impractical as a set of parameters need to be estimated for each country separately. To overcome this problem, the *random-effects approach* in multilevel modeling (Laird & Ware, 1982; Searle, Casella, & McCulloch, 1992; Verbeke & Molenberghs, 2000), has been proposed and has increased in popularity in the past decade. The random-effects approach considers a set of countries sampled from a larger population. Instead of estimating parameters for each country separately, a distribution of parameter values is assumed to account for the variability between countries.

The basis for and new developments in both latent variable modeling and multilevel modeling as applied to cross-cultural comparisons have been reviewed in several recent books (e.g., Davidov, Schmidt, & Billiet, 2011; Matsumoto & van de Vijver, 2011; van de Vijver et al., 2008). These models primarily explore the basis cultural differences, but they do not allow a full exploration of cross-cultural similarities and differences because each cultural type was assumed to be internal homogeneous. The two-level latent class model (TL-LCM) is proposed in this article as an analysis framework for exploring cross-cultural similarities and differences. As will be discussed later, the two main characteristics of TL-LCM, a typological and probabilistic model, allow it to have major advantages over traditional dimensional models (which assume continuous latent constructs) and deterministic models (which assume homogeneity within a country).

In the following sections, the typological and probabilistic characteristics of the TL-LCM will be discussed in contrast to the traditional dimensional and deterministic approaches for cross-cultural comparisons. Next, the specifications of the proposed model are presented as well as the discussion of parameter estimations. Two empirical data examples are used to illustrate the flexibility and usefulness of applying the TL-LCM to empirical data. A discussion of the applications, extensions, and limitations are then presented; the article concludes with some remarks on methodological considerations and empirical applications of the TL-LCM for exploring cross-cultural differences.

Typological Versus Dimensional Modeling Approach

Latent variable models are flexible methodological tools for cross-cultural studies (e.g., Little, 1997; van de Vijver & Leung, 1997, 2000). These statistical methods usually assume latent continuity of the pertinent constructs, so they are also called dimensional models. Dimensions of cultural variation have been called "cultural syndromes" (Triandis, 1993), and one of the most discussed cultural syndrome is the collectivism–individualism dimension (e.g., Brewer & Chen, 2007; Triandis, 1996). Specifically, individualism and collectivism can be considered as two ends of a one-dimensional latent continuum, and cultural groups can be placed along this underlying dimension.

The dimensional theories are commonly assumed in research of cross-cultural differences. The comparison of typological structures between cultures has been attempted only rarely. The exceptions are articles by Eid and Diener (2001) as well as by Eid, Langeheine, and Diener (2003). The second article gives a nice overview of latent class analysis and discusses the usefulness of such a typological model for cross-cultural studies. Eid et al. (2003) used multiple-group latent class analysis, analyzing the latent structures separately for each country, to demonstrate the advantages of applying latent class analyses for cross-cultural comparisons. The typological approach used by Eid et al. (2003) assumes that each country belongs to a unique latent cultural type, and individuals within that country have similar characteristics that are specific to that country. For example, China was exemplified as a relatively collectivistic country, and the United States as a relatively individualistic one for applying multiple-group latent class analysis in Eid et al. (2003).

Comparing typological structures between different cultural groups can be used to study cross-cultural differences; however, this approach has not been commonly used except the work by Eid and colleagues (Eid & Diener, 2001; Eid et al., 2003). This might be partly because psychologists in cross-cultural studies are unfamiliar with the available methodologies suitable for comparing typological structures between cultures. The TL-LCM proposed in this article can be a tool of comparing latent typological structures between cultural groups.

Probabilistic Versus Deterministic Modeling Approach

Most standard statistical models typically applied in cross-cultural studies assume homogeneity within each cultural group. For example, the factor loadings in factor analysis (FA) or SEM are assumed to be identical for individuals in the same culture. The assumption of intracultural homogeneity is deterministic, as a fixed value was attached to each individual within a group. This assumption is simple, but it is also very strong and usually not a fulfilled assumption (e.g., Rost & Langeheine, 1997).

The TL-LCM proposed in this article is a probabilistic model. In other words, each individual has a probability of belonging to one latent group (latent class). The probabilistic model is opposed to the traditional determinist model because each country does not deterministically belong to a specific latent cluster and each individual does not deterministically belong to a specific latent class. The probabilistic aspect offers flexibility in conceptualizing the cultural differences by allowing heterogeneity within a country, which also avoids the usual unrealistic assumption of intracultural homogeneity commonly found in traditional statistical methods.

Specifically, the TL-LCM assumes that different probabilities to categorize each individual into latent classes and country into latent clusters. For example, individuals have different likelihoods, or probabilities, of being "idiocentrism" and "allocentrism" (individual-level latent classes) and countries have different probabilities of being "individualism" and "collectivism" (country-level latent clusters). A certain degree of uncertainty about latent class membership allows a better representation of general theoretical hypotheses because it accommodates better the heterogeneity among individuals and individual differences.

TL-LCM

The proposed TL-LCM is a typological model for which discrete latent constructs are assumed. The standard models that assume discrete latent variables are latent class models (LCMs) for categorical response variables and latent profile models (LPMs; Lazarsfeld & Henry, 1968) for metrical response variables. LCMs and LPMs have been made more popular by several articles which proposed alternative parameterization, computational algorithms, and provided programs for estimating model parameters (e.g., Clogg, 1995; Clogg & Goodman, 1984; Hagenaars, 1993; Langeheine & Rost, 1988; Rost & Langeheine, 1997). The TL-LCM assumes discrete latent variables as in LCM and LPM to explain the observed dependency between item responses.

The data structure in a typical study of cross-cultural comparison has two levels: countries and individuals. The advantage of the TL-LCM is that discrete latent constructs are assumed at both the country (higher) and individual (lower) levels instead of only at one level. The discrete latent structure at the country level is referred as "latent clusters," which can be conceptualized as distinct and internally homogeneous cultural types, and each country has a specific likelihood to be categorized into each of the latent clusters. The discrete latent structure at the individual level is referred as the "latent class," which represents homogeneous latent subgroups of individuals. Because each individual has a different probability of being classified into each of these latent classes and each country has a different probability of being classified into each of latent clusters, the composition (and size) of the latent classes may be different within each latent cultural type (i.e., within each country-level cluster). These unique compositions of latent classes thus can be used to contrast the differences between cultural types. For example, in Country A, the probabilities of individuals from the collectivistic, individualistic, or non-classifiable classes are .6, .3, and .1, respectively, but in Country B, the respective probabilities are .2, .7, and .1.

Specifications of the TL-LCM

The TL-LCM is a very flexible methodological tool for analyzing inter- and intra-country differences using discrete latent variables. It is formally defined in this section using the typical terminology of cross-cultural studies. The model is specified separately at the country and individual levels, and then the two levels are linked based on the assumed dependency due to the nested data structure.

At the country level, let the latent variable H_c denote a discrete latent variable. It is assumed to have L latent clusters representing the L distinct latent cultural types. Each country is assumed to come from one of these latent clusters. The subscript c identifies the specific country, and $c = 1, \ldots, C$ indicates a total of C observed countries. The vector $\mathbf{y}_{c_i}$ represents the responses of the J item responds from the i th individual in the c th country, and $\mathbf{y}_c$ denotes the full vector of responses for all individuals of the c th country. The probability of observing responses from all individuals of Country c to all items is

$$P(\mathbf{y}_c) = \sum_{l=1}^{L} P(H_c = l) P(\mathbf{y}_c \mid H_c = l). \tag{1}$$

The term $P(H_c = l)$ is the latent cluster probability. It follows a multinomial distribution that describes the distribution of latent clusters and can be thought of as representing cluster sizes. The term $P(\mathbf{y}_c \mid H_c = l)$ is the response probability of items conditioned on latent cluster membership.

At the individual level, let X_i denote a second discrete latent variable. It is assumed to have M latent classes representing the M distinct subgroups of individuals. Each individual is assumed to come from one of these latent classes. The subscript identifies the specific individual. When a questionnaire of J items was administered to all individuals, the response vector of each individual is denoted as $\mathbf{y}_i$, and the element of this vector (y_i^j) is each item's response. Regardless of the nested data structure, a LCM is formed at the individual level. The probability of observing the response pattern $\mathbf{y}_i$ for subject i is

$$P(\mathbf{y}_i) = \sum_{m=1}^{M} P(X_i = m) P\left(y_i^j \mid X_i = m\right). \tag{2}$$

The term $P(X_i = m)$ is the latent class probability, and $P(y_i^j \mid X_i = m)$ is the class-specific density function, the form of density depending on the assumed distribution of y (e.g., binomial, multinomial, or normal); this term is also referred to as conditional response probability. The usual local independent assumption is assumed and is represented by the multiplication of all probabilities of the J items conditioning a particular latent class.

Data observed from the same unit tend to be correlated. To accommodate the dependency due to the nested data structure, each individual is differentiated by the subscript of Country c as c_i. This index represents each individual's higher level (country) membership. Equation 2 is rewritten with these specifications for group membership:

$$P(\mathbf{y}_{c_i}) = \sum_{m=1}^{M} P(X_{c_i} = m) \prod_{j=1}^{J} P\left(y_{c_i}^j \mid X_{c_i} = m\right). \tag{3}$$

The dependency between levels is linked in that $P(X_{c_i} = m)$ depends on the higher level latent cluster and is represented by the conditional probability of $P(X_{c_i} = m \mid H_c = l)$. Conceptually, this expression suggests that each latent cluster has a unique composition of latent classes, or simply, the sizes of these classes vary across latent clusters. Moreover, like the local independency assumed at the individual level, the responses of individuals in the same country are also assumed to be independent of each other, given their latent cluster membership. Finally, the latent cluster membership is assumed to have no effect on how the items were responded to in order to avoid the possible confusion of attributing the effects of how each item was responded to. Of course, it is possible that cultural types may directly affect individuals' response styles. Specifically, it is to allow the latent cluster membership to have impact on item response probabilities (i.e., $P(y_i^j \mid X_i = m, H_c = l)$). However, having both cultural and individual effects would entangle the attributions of effects and interpretations of results. As a result, the TL-LCM assumes that there is no direct effect from group level to the conditional response probabilities (i.e., $P(y_{c_i}^j \mid X_{c_i} = m)$). This assumption not only simplifies the model so that it has fewer parameters to estimate, but it also contributes to more intuitive interpretations of influential sources.

With these assumptions, Equation 3 can be rewritten as

$$P(\mathbf{y}_c \mid H_c = l) = \prod_{i=1}^{n_c} \left(\sum_{m=1}^{M} P(X_{c_i} = m \mid H_c = l) \prod_{j=1}^{J} P\left(y_{c_i}^j \mid X_{c_i} = m\right) \right), \tag{4}$$

where n_c denotes the number of individuals for the c th country. With these specifications, the probability of observing responses of $\mathbf{y}_c$ defined at the country level is

$$P(\mathbf{y}_c)=\sum_{l=1}^{L}\left(P(H_c=l)\prod_{i=1}^{n_c}\left[\sum_{m=1}^{M}P\left(X_{c_i}=m\mid H_c=l\right)f\left(\mathbf{y}_{c_i}\mid X_{c_i}=m\right)\right]\right). \tag{5}$$

The proposed TL-LCM might seem like it resembles a version of the multilevel extension of the LCM, the multilevel latent class model (MLCM), proposed by Vermunt (2003). The MLCM extends from traditional multilevel modeling by introducing random effects at the higher level to account for the dependency due to the nested data structure. In the MLCM, the higher level effects used to account for group effects can come from either parametric or non-parametric distributions. The TL-LCM discussed in this article is conceptually different from Vermunt's in how the group-level effects are conceptualized. In Vermunt's multilevel extension, group-level differences in lower level parameters are explained by introducing higher level random effects. However, the TL-LCM can be conceptualized as two layers of LCMs applied to observed countries and individuals simultaneously. In other words, Vermunt's MLCM emphasizes capturing and measuring the effects attributable to the nested data structure, but the TL-LCM proposed here emphasizes the classification and clustering of countries into latent clusters and individuals into latent classes. Specifically, the TL-LCM is not rooted in the traditional multilevel modeling framework that makes distribution assumptions for the effects at higher levels, but rather it focuses mainly on exploring the latent structure of the sampled countries. Despite these differences described above, mathematically speaking, TL-LCM and MLCM are equivalent in terms of the number of parameters and the methods used to estimate these parameters. Therefore, in this sense, these two models can be regarded as parallel development.

The parameters of the proposed TL-LCM are estimated using the modified expectation–maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977). The standard EM algorithm was found to be impractical in the context of multilevel modeling; therefore, the E-step is modified using the upward–downward algorithm (Vermunt, 2002, 2003, 2004). The upward–downward algorithm is analogous to the forward–backward algorithm, or Baum–Welch algorithm, for the estimation of hidden Markov models with a large number of time points (Baum, Petrie, Soules, & Weiss, 1970; Frühwirth-Schnatter, 2006). Details of the parameter estimation procedure can be found in Yu (2007). The proposed TL-LCM can be estimated using the freely available MATLAB MDLV toolbox (Yu, 2013) and Latent Gold 4.5 with the syntax module (Vermunt & Magidson, 2008). The available toolbox and software make the TL-LCM described here accessible to researchers who would like to apply a typological and probabilistic rather than a deterministic approach to studying cross-cultural differences and similarities.[1]

Illustrative Examples

Two examples are used to illustrate how TL-LCM can be applied to analyze empirical data. These two examples also demonstrate the steps of applying TL-LCM for exploratory purposes, as well as how the estimated parameters of TL-LCM are interpreted in a specific research context.

Example 1: The European Values Study (EVS)

The EVS (2011) consisted of four waves of surveys between 1981 and 2008. The aims of the EVS were to explore the moral and social values of Europeans, including topics such as attitudes toward family, work, religion, politics, and society. Further information about this study is

Table 1. The Estimated Parameters for the Two-Cluster and Four-Class Model (Model 3).

	Item	Class 1	Class 2	Class 3	Class 4
1	Good manners	0.66	0.25	0.77	0.99
2	Independence	**0.21**	**0.51**	*0.09*	0.86
3	Hard work	0.23	0.20	0.13	0.74
4	Feeling of responsibility	**0.48**	0.59	*0.09*	0.93
5	Imagination	0.06	**0.27**	0.05	0.68
6	Tolerance and respect for other people	0.37	0.67	**0.63**	0.80
7	Thrift, saving money and things	**0.27**	0.08	*0.03*	0.99
8	Determination, perseverance	0.09	**0.31**	0.09	0.99
9	Religious faith	0.24	0.06	0.34	0.78
10	Unselfishness	0.11	0.17	**0.32**	0.87
11	Obedience	0.27	0.00	**0.51**	0.98

	Two clusters and two classes
Latent cluster probabilities	$P(H_c\!=\!1) = \begin{bmatrix} .79 \\ .21 \end{bmatrix}$
Conditional latent class probabilities	$P(X \mid H) = \begin{bmatrix} .64 & .16 \\ .30 & .13 \\ .05 & .70 \\ .01 & .00 \end{bmatrix}$

available at the EVS website (www.europeanvaluesstudy.eu). To demonstrate the usefulness of the TL-LCM, I used data from the first wave (1981 survey) about the values that parents consider especially important for children to learn at home.

Participants were presented with the following question: "Here is a list of qualities which children can be encouraged to learn at home. Which, if any, do you consider to be especially important? Please choose up to five." If a quality was selected, then it was coded as 1 (important); otherwise, it was coded as 0 (not selected). In the first wave, 17 qualities were provided; however, only the 11 qualities (see Table 1) that were common across all four waves were used in the following illustration.

In the first wave, there were 16 countries with different numbers of participants from each country. To have an equal representation from each country, 100 participants were randomly sampled therein. As a result, a total of 1,600 participants with their 11 binary responses (important and not mentioned) regarding qualities important to teach children were included in this analysis.

Using TL-LCM, the data were fit to 16 different models with a latent structure of two to five clusters in a combination of two to five classes. These 16 models cover wide range of potential latent structures observed in practice. The fit statistics of the estimated models are presented in Table 2. According to Bayesian information criterion (BIC) and consistent Akaike information criterion (CAIC), the best-fit model is the two-cluster and four-class model, and Akaike information criterion (AIC) and AIC3 prefer the four-cluster and five-class model. The two-cluster and four-class model is picked as the final model based on preference for a parsimonious model (fewer classes and clusters) and the interpretable pattern of the estimated parameters. The estimated parameters of this model are reported in Table 1.

The estimated conditional response probabilities of the four classes are listed in Table 1. Individuals in Class 3 have a higher probability than individuals in Class 1 (more than .2 in terms

Table 2. The BIC, AIC, AIC3, and CAIC Value of the EVS Data Fit to the 16 TL-LCMs.

Model	L	M	BIC	AIC	AIC3	CAIC
1	2	2	18,906	18,772	18,797	18,931
2		3	18,862	18,658	18,696	18,900
3		4	**18,780**	18,505	18,556	**18,831**
4		5	18,806	18,462	18,526	18,870
5	3	2	18,895	18,749	18,776	18,922
6		3	18,831	18,610	18,651	18,872
7		4	18,818	18,522	18,577	18,873
8		5	18,817	18,445	18,514	18,886
9	4	2	18,903	18,747	18,776	18,932
10		3	18,824	18,587	18,631	18,868
11		4	18,806	18,488	18,547	18,865
12		5	18,780	**18,382**	**18,456**	18,854
13	5	2	18,911	18,744	18,775	18,942
14		3	18,828	18,575	18,622	18,875
15		4	18,808	18,469	18,532	18,871
16		5	18,822	18,397	18,476	18,901

Note. "L" and "M" indicate the number of latent clusters and classes of a TL-LCM. The lowest value of the 16 models for each information criterion was indicated in bold. BIC = Bayesian information criterion; AIC = Akaike information criterion; CAIC = consistent Akaike information criterion; EVS = European values study; TL-LCM = two-level latent class model.

of probability) to pick items (6) tolerance and respect for other people, (10) unselfishness, and (11) obedience, as important qualities for children to learn. In contrast, individuals in Class 3 rarely considered the qualities of (2) independence, (4) feeling of responsibility, and (7) thrift, saving money and things, as qualities important for children to learn at home. Thus, Class 3 can be considered to value more "collective" qualities. In contrast, individuals in Class 2 are characterized as having relatively higher importance ratings on item (2) independence, (5) imagination, and (8) determination or perseverance. Therefore, Class 2 values more "individualistic" qualities. However, Class 1 values qualities mixed between Class 2 and Class 3, and is called the "balanced" class. Class 4 is a very small class (about 1% of the total individuals) that corresponds to individuals who believe every listed quality is important and have no discrimination among the importance of these qualities.

The estimated latent cluster probabilities and conditional latent class probabilities for the two-cluster and four-class solution are presented in the lower panel of Table 1. At the country level, this model suggested a larger cluster (Cluster A), consisting of 79% of the participating countries, and a smaller cluster (Cluster B), consisting of 21% of the countries. For Cluster A, the estimated conditional latent class probabilities showed a dominant Class 1 (64%), a sizable Class 2 (30%), and small Class 3 (5%) and Class 4 (1%). In contrast, Cluster B has a dominant Class 3 (70%). Classes 1 and 2 were estimated at 16% and 13%, respectively, and Class 4 was close to 0.

Based on the responses of individuals from each country, each country can be assigned to the one cluster for which it has a higher posterior latent cluster probability. This classification of the latent cluster membership for the 16 countries is listed in Table 3. The majority of participating countries were categorized into Cluster A; the three countries categorized into Cluster B were Ireland, Great Britain, and Northern Ireland. The meanings of Cluster A and Cluster B can be interpreted and understood through the relative size of classes within a cluster as well as the unique characteristics associated with each latent class. Specifically, the two clusters can be differentiated based on the class which dominates it.

Table 3. The Predicted Latent Cluster Membership for the 16 Countries.

	Country	Cluster
1	Belgium	A
2	Canada	A
3	Denmark	A
4	France	A
5	Germany	A
6	Great Britain	B
7	Iceland	A
8	Ireland	B
9	Italy	A
10	Malta	A
11	The Netherlands	A
12	Northern Ireland	B
13	Norway	A
14	Spain	A
15	Sweden	A
16	USA	A

Analyzing this data set using the TL-LCM clearly revealed two clusters of countries, and parents from each cluster have different patterns and types in their value system of parenting. Countries in Cluster A has a dominant "balanced" class in values to teach their children, whereas countries in Cluster B has a dominant "collective" class. However, about 30% of the individuals did not fit into the dominant class in each cluster.

Example 2: Contextualism Beliefs

For the second example, I use data from a study on motivated identity construction in a cultural context (Vignoles & Brown, 2011). Contextualism beliefs of individuals in 35 countries were measured by 14 items that cover the importance of a range of different contexts: family, social groups, position in society, the place one comes from, occupation, where one lives, social position, role in society, and educational achievement (Owe et al., 2013); these items are described in Table 4.[2] Items were rated on 6-point scales ranging from 1 (*completely disagree*) to 6 (*completely agree*), items are treated as continuous variables in the present analysis.

Again, 16 models (two-five clusters and two-five classes) were fit to the data for exploratory purposes. The log-likelihood and fit statistics of the estimated models are presented in Table 5. According to AIC and BIC, the best fit is the two-cluster and five-class model (Model 4). However, when examining the pattern of conditional response probabilities, the two-cluster and five-class solution differs only in the patterns of a few items but without meaningful interpretation for such differences. The patterns also suggested that a simpler two-class solution (Model 1) might be a good representation for the structure of latent classes. In addition, the pattern of the estimated parameters for the three-cluster and two-class solution (Model 5) also shows some interesting patterns regarding its latent structure. The two models (Models 1 and 5) are chosen for interpreting the latent structure of the data. Table 4 summarizes the estimated rating of each item for Class 1 and Class 2, as well as the estimated latent cluster probabilities and conditional latent class probabilities of the two models.

Both Model 1 and Model 5 suggest a two-class solution at the individual level. According to the estimated ratings of two classes, individuals in Class 1 have higher estimated ratings on items

Table 4. The Estimated Parameters of Models of Two Classes With Two and Three Clusters.

		(Model 1) Two clusters–two classes	(Model 5) Three clusters–two classes
Latent cluster probabilities		$P(H_c = 1) = \begin{bmatrix} .27 \\ .73 \end{bmatrix}$	$P(H_c = 1) = \begin{bmatrix} .21 \\ .50 \\ .29 \end{bmatrix}$
Conditional latent class probabilities		$P(X \mid H) = \begin{bmatrix} .26 & .61 \\ .74 & .39 \end{bmatrix}$	$P(X \mid H) = \begin{bmatrix} .24 & .55 & .71 \\ .76 & .45 & .29 \end{bmatrix}$
	Items	Class 1	Class 2
1	To understand a person well, it is essential to know about his or her role in society.	*3.36*	*4.74*
2	You cannot really change your deepest attributes.	3.91	4.37
3	One can understand a person well without knowing about his or her social position.	**4.27**	**3.34**
4	You can always substantially change the kind of person you are.	3.26	3.42
5	One can understand a person well without knowing about the place he or she comes from.	**4.29**	**3.36**
6	No matter what kind of person you are, you can always change a lot.	3.68	3.76
7	To understand a person well, it is essential to know about his or her family.	*2.95*	*4.68*
8	You can do things differently, but the important parts of who you are cannot really be changed.	4.07	4.47
9	To understand a person well, it is essential to know about which social groups he or she is a member of.	*2.85*	*4.57*
10	You can change even your most basic qualities.	2.97	3.26
11	To understand a person well, it is essential to know about the place he or she comes from.	*2.51*	*4.51*
12	The kind of person you are is something very basic about you and it cannot be changed very much.	3.74	4.20
13	One can understand a person well without knowing about his or her family.	**4.14**	**3.27**

Table 5. Fit Indices of the 16 Models Fitted to Contextualism Beliefs Data Example.

Model	L	M	BIC	AIC	AIC3	CAIC
1	2	2	302,392	302,019	302,074	302,447
2		3	293,924	293,361	293,444	294,007
3		4	290,751	289,999	290,110	290,862
4		5	**289,366**	**288,424**	**288,563**	**289,505**
5	3	2	302,350	301,964	302,021	302,407
6		3	296,976	296,393	296,479	297,062
7		4	291,843	291,063	291,178	291,958
8		5	290,631	289,655	289,799	290,775
9	4	2	302,354	301,954	302,013	302,413
10		3	296,783	296,179	296,268	296,872
11		4	293,041	292,235	292,354	293,160
12		5	291,317	290,307	290,456	291,466
13	5	2	302,366	301,953	302,014	302,427
14		3	296,760	296,136	296,228	296,852
15		4	292,966	292,133	292,256	293,089
16		5	290,721	289,677	289,831	290,875

Note. "L" and "M" indicate the number of latent clusters and classes of a TL-LCM. The lowest value of the 16 models for each information criterion was indicated in bold. BIC = Bayesian information criterion; AIC = Akaike information criterion; CAIC = consistent Akaike information criterion; TL-LCM = two-level latent class model.

3, 5, and 13 among the 13 items than Class 2. These three items are relating to the idea that we do not need to know a person's social position, where he or she came from, or his or her family to understand them. Class 2, however, rated higher for items related to the idea that it is essential to understand someone through his or her family, origin, social role, and membership in social groups. Although there are some minor differences on other items, the main distinctions are the items mentioned above. With these observations, individuals in Class 1 can be referred to as "individual-oriented" class and individuals in Class 2 as "collective-oriented" class with respect to their attitudes toward how to understand others.

The two-cluster and two-class solution (Model 1). The estimated latent cluster probabilities for the two-cluster and two-class solution are presented in the bottom panel of Table 4. At the country level, the results suggested a larger cluster (Cluster A), consisting of 73% of the participating countries, and a smaller cluster (Cluster B), consisting of 27% of the countries. Based on the responses of individuals from each country, the posterior probabilities of a given country belonging to each of the clusters were calculated. Each country is then categorized into the cluster that has the higher posterior latent cluster probability.[3] The resulting latent cluster classifications of the 34 countries are presented in Figure 1. The nine countries categorized in Cluster A are China, Ethiopia, Malaysia, Philippines, Singapore, Uganda, Turkey, Peru, and Thailand. The other 25 countries were grouped in Cluster B.

For Cluster A countries, the estimated conditional latent class probabilities showed that 74% of the individuals were in Class 2 (collective-oriented class), and 26% were in Class 1 (individual-oriented class). The reverse held for Cluster B: 61% of the individuals were in Class 1 (individual oriented) and 39% in Class 2 (collective oriented). This pattern is consistent with the typical individualism–collectivism distinction. However, the proposed model allows some variations from the prototypes at both the individual and country levels as for generally collective-oriented countries (Cluster A), 26% of the individual respondents (Class 1) did not fit the typical collective-oriented profile, and for the generally individual-oriented countries (Cluster B) 39% of

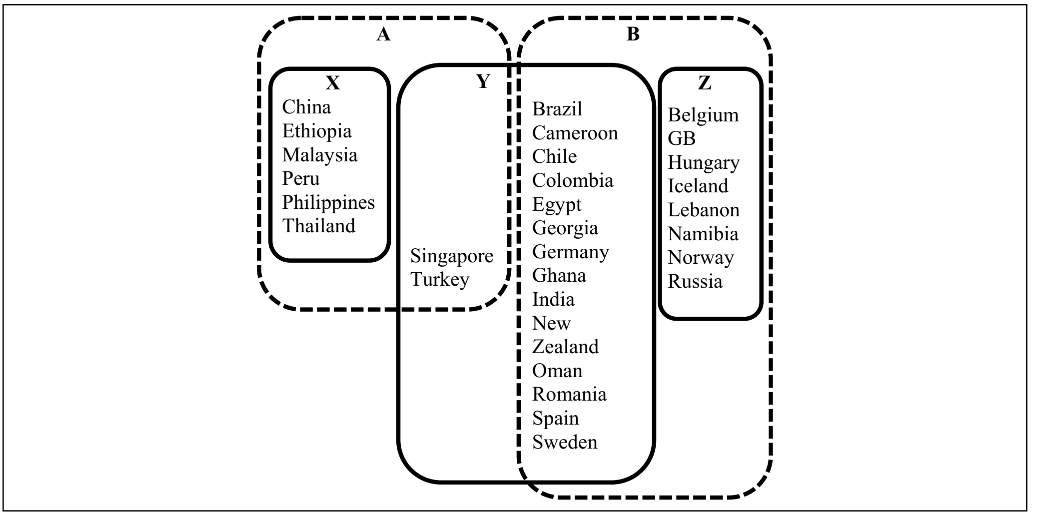

Figure 1. The representation of the predicted latent cluster membership for the two-cluster two-class model (Model 1) in dashed lines (A, B), and for the three-cluster two-class model (Model 5) in solid lines (X, Y, Z).

individuals did not fit the typical individual-oriented profile (Class 2). Allowing individuals to deviate from the standard latent classes or clusters is one major advantage of the proposed model, as this variability is more consistent with what is usually observed empirically.

The three-cluster and two-class solution (Model 5). The three-cluster solution suggests there is a major cluster consisting of about half of the participating countries, and the other two clusters consist of about 29% and 21% of the countries. Figure 1 illustrates the groupings of the 34 countries for their predicted latent cluster memberships. The three clusters are labeled as clusters X, Y, and Z. Based on the countries in the clusters, countries grouped in Cluster X (21% of countries) are similar to the previous countries of Cluster A in the two-cluster solution, except that Singapore and Turkey are no longer included. The original Cluster B is divided into Cluster Y (50% of countries, but now with Singapore and Turkey) and Cluster Z (29% of countries).

As Cluster A in the two-cluster solution, Cluster X consists of countries with mostly collective-oriented individuals (76% Class 2), whereas Cluster Z consists of countries with mostly individual-oriented individuals (71% Class 1). Cluster Y consists of countries in which individuals are roughly equally split between collective (55%) and individual oriented (45%). The three-cluster solution offers finer differentiation between countries along the general individual-oriented continuum.

In summary, In Model 1, with two clusters, Cluster A contains countries with individuals who tend to respond collectively whereas Cluster B contains countries with individuals who tend to respond individualistically. In Model 5, with three clusters, X are countries containing individuals with collective responses, Z are countries containing individuals with individualistic responses, and Y are countries where individuals are more evenly split between collectivist and individualistic responses. These results are consistent with the original study by Owe et al. (Owe et al., 2013) on personhood beliefs: contextualism is an important facet of individualism–collectivism. Specifically, the contextualism is an important component of cultural collectivism. The analyses using the TL-LCM relaxes the assumption of within-cultural homogeneous, and allows researchers to examine the finer differences among comparing countries.

Discussion

The main purpose of applying TL-LCM for exploratory purposes is to account for the observed dependency in collected data through identifying the appropriate latent structure of latent clusters and classes. The purpose of exploratory analysis is to select the best-fit model among several candidate models with the goal of better understanding the structure of the data, for example, to discover how many unique cultural types exist among countries regarding the attitude toward religious belief. When the data contain hierarchical dependencies (e.g., individuals within countries), the TL-LCM is ideal for these exploratory purposes as it can account for these hierarchical dependencies by identifying the appropriate latent structure of latent clusters and lower level classes.

Moreover, TL-LCM can serve a confirmatory purpose when used to confirm hypotheses about latent structure, specifically, whether the observed data support the hypothesized latent structure. For example, two culture types, individualism and collectivism, can be considered as two latent clusters at the country level. A confirmatory TL-LCM can be used to examine whether the two latent clusters model have a better fit than other models with different latent structures.

In cross-cultural research, one important issue is the equivalence between two countries. Establishing equivalence is critical for allowing meaningful comparisons and interpretations about the similarities and differences between the countries. The standard objective in cross-cultural research is to achieve all levels of equivalence so the differences between cultures can be meaningfully and directly compared (Fontaine, 2005; van de Vijver & Leung, 1997). In practice, it is very difficult to achieve all levels of equivalence in the analysis of empirical data for many possible reasons including differences in language, wording, or response styles across cultures.

The TL-LCM handles the issue of equivalence somewhat differently from the traditional methods of analysis. The traditional methods assume two comparing cultural types are internal homogeneous. However, the TL-LCM relaxes this internal homogeneous assumption by allowing variation in each cultural type. Allowing within-cultural heterogeneity provides additional information to understand the differences between cultural types: First, each country has a probability of being categorized into a latent cluster, and each individual has a probability of being categorized into a latent class. Consequently, the prevalence or size of these latent constructs reveals the differences and similarities between cultural types. Second, an identical measurement model (pattern of conditional response probabilities of items) is associated with a particular latent class across latent clusters, but each individual's latent class membership is not deterministic but probabilistic. As a result, the TL-LCM handles the issue of equivalence in cross-cultural comparisons by incorporating the heterogeneity in the model instead of treating it as "errors."

The TL-LCM may be further developed to relax the assumption of assuming identical measurement model associated with each class, so that the measurement equivalence between cultures can be assessed. This possible extension may lead to a much complex model (i.e., many more parameters), but adding constraints on the latent structure and/or measurement model may make the model feasible for parameter estimations. This direction is an avenue for future research and beyond the scope of the current article.

In the context of multilevel SEM, ideas of including covariates or contextual variable to explain cultural differences (or item biases) had been recently proposed (e.g., Davidov, Dülmer, Schlüter, Schmidt, & Meuleman, 2012; Jak, Oort, & Dolan, 2013). Similar extension of including covariates or contextual variables can be applied to TL-LCM. For example, including a measure of social desirability can reduce the bias when measuring the individuals' altitude toward sensitive issues. A second extension is to allow more than two levels within a nested data structure. For example, age groups could be included between the country and individual levels to form a three-layer data structure. An additional layer of discrete latent variables may allow us to gain additional understanding about the latent structure of the data. The proposed TL-LCM has some limitations when used to explore cross-cultural differences. First, data with cross-classified and multiple membership structure cannot be accommodated in the current TL-LCM. One example of this is when an individual has multiple citizenships. Second, the numbers and characteristics of latent classes are assumed to be the same for each latent cluster. As a result, theories that explicitly assume different latent classes within each latent cluster cannot be analyzed using the TL-LCM.

Conclusion

Discrete latent constructs are useful and versatile tools when applied to theories or hypotheses typically made in cultural psychology. The TL-LCM proposed in this article offers an analytical framework using discrete latent variables for underlying typological structure. Instead of being bound with dimensional assumptions of latent constructs, the TL-LCM allows researchers to form alternative typological hypotheses about the latent constructs. In addition, the TL-LCM provides a probabilistic approach to studying the latent structures simultaneously at two nested levels. The probabilistic characteristic of the TL-LCM also relaxes the strong and often unrealistic assumption that individuals within the same higher level cluster (country) are homogeneous.

Two examples demonstrated the usefulness and flexibility of applying the TL-LCM to analyze nested cross-cultural data. The examples showed that differences between cultural types (countries) can be thought of as arising from the fact that individuals within different countries have different probabilities of falling into one of multiple classes, rather than assuming that the individuals within each country are homogeneous.

In summary, the typological and probabilistic characteristics of the TL-LCM offer several advantages over the traditional dimensional and deterministic models commonly used in cross-cultural research. A holistic interpretation of observed phenomena at both the country and individual levels can be achieved as both levels are modeled simultaneously in the TL-LCM. Therefore, the TL-LCM not only offers researchers new potential perspectives in exploring differences between cultures, but it also facilitates the process of forming theories and hypotheses so that knowledge and understanding of cultural differences and similarities can be further advanced. For example, researchers can use the clusters map similar to Figure 1 to stimulate new theories or generate alternative hypotheses.

Acknowledgment

Special thanks to Kris Onishi for her helpful discussion and comments in the preparation of this manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was supported by National Sciences and Engineering Research Council of Canada (NSERC) Discovery Grants PGPIN 391334.

Notes

1. The categorical latent variable defined in the two-level mixture model (Asparouhov & Muthén, 2008) is by discretizing an underlying normally distributed latent variable. Therefore, it is conceptually different from the proposed TL-LCM in this article. If researchers are willing to make such assumption

about the categorical latent variable, a model similar to TL-LCM can be specified and estimated by Mplus.

2. Only data of 13 items from 34 countries are available in the online database, the analyses done here were based on this available data set.
3. In Latent Gold, this information can be obtained by requesting posterior classification in output menu.

References

Asparouhov, T., & Muthén, B. (2008). Multilevel mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 27-51). Charlotte, NC: Information Age Publishing.

Baum, L. E., Petrie, T., Soules, G., & Weiss, N. (1970). A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *Annals of Mathematical Statistics*, *41*, 164-171.

Brewer, M. B., & Chen, Y. R. (2007). Where (who) are collectives in collectivism? Toward conceptual clarification of individualism and collectivism. *Psychological Review*, *114*, 133-151.

Clogg, C. C. (1995). Latent class models. In G. Arminger, C. C. Clogg, & M. E. Sobel (Eds.), *Handbook of statistical modeling for the social and behavioral sciences* (pp. 311-359). New York, NY: Plenum.

Clogg, C. C., & Goodman, L. A. (1984). Latent structure analysis of a set of multidimensional contingency tables. *Journal of the American Statistical Association*, *79*, 762-771.

Davidov, E., Dülmer, H., Schlüter, E., Schmidt, P., & Meuleman, B. (2012). Using a multilevel structural equation modeling approach to explain cross-cultural measurement noninvariance. *Journal of Cross-Cultural Psychology*, *43*, 558-575.

Davidov, E., Schmidt, P., & Billiet, J. (Eds.). (2011). *Cross-cultural analysis: Methods and applications*. New York, NY: Routledge.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood estimation from incomplete data via the EM algorithm (with discussion). *Journal of the Royal Statistical Society, Series B*, *39*, 1-38.

Eid, M., & Diener, E. (2001). Norms for affect in different cultures: Inter- and intraindividual differences. *Journal of Personality and Social Psychology*, *81*, 869-885.

Eid, M., Langeheine, R., & Diener, E. (2003). Comparing typological structures across cultures by latent class analysis: A primer. *Journal of Cross-Cultural Psychology*, *34*, 195-210.

European Values Study. (2011). *European values study 1981-2008, longitudinal data file* (GESIS Data Archive, Cologne, Germany, Study No. ZA4804, Data File Version 2.0.0 [2011-12-30]). doi:10.4232/1.11005

Fischer, R. (2009). Where is culture in cross cultural research? An outline of a multilevel research process for measuring culture as a shared meaning system. *International Journal of Cross Cultural Management*, *9*, 25-49. doi:10.1177/1470595808101154

Fontaine, J. R. (2005). Equivalence. In K. Kempf-Leonard (Ed.), *Encyclopedia of social measurement* (Vol. *I*, pp. 65-92). New York, NY: Academic Press.

Fontaine, J. R. (2008). Traditional and multilevel approaches in cross-cultural research: An integration of methodological frameworks. In F. J. R. van de Vijver, D. A. van Hemert, & Y. Poortinga (Eds.), *Individuals and cultures in multilevel analysis* (pp. 65-92). Mahwah, NJ: Lawrence Erlbaum.

Frühwirth-Schnatter, S. (2006). *Finite mixture and Markov switching models*. New York, NJ: Springer.

Hagenaars, J. A. (1993). *Loglinear models with latent variables*. Newbury Park, CA: Sage.

Hofstede, G. (1980). *Culture's consequences: International differences in work related values*. Beverly Hills, CA: Sage.

Hox, J. (2002). *Multilevel analysis: Techniques and applications*. Mahwah, NJ: Lawrence Erlbaum.

Jak, S., Oort, F. J., & Dolan, C. V. (2013). A test for cluster bias: Detecting violations of measurement invariance across clusters in multilevel data. *Structural Equation Modeling*, *20*, 265-282.

Laird, N. M., & Ware, J. H. (1982). Random effects models for longitudinal data. *Biometrics*, *38*, 963-974.

Langeheine R., & Rost, J. (Eds.). (1988). *Latent trait and latent class models*. New York, NY: Plenum.

Lazarsfeld, P. F., & Henry, N. W. (1968). *Latent structure analysis*. Boston: Houghton.

Little, T. D. (1997). Mean and covariance structures (MACS) analyses of cross-cultural data: Practical and theoretical issues. *Multivariate Behavioral Research*, *32*, 53-76.

Matsumoto, D., & van de Vijver, F. J. R. (Eds.). (2011). *Cross-cultural research methods in psychology*. New York, NY: Cambridge University Press.

Owe, E., Vignoles, V. L., Becker, M., Brown, R., Smith, P. B., Lee, S. W. S., . . .Jalal, B. (2013). Contextualism as an important facet of individualism-collectivism: Personhood beliefs across 37 national groups. *Journal of Cross-Cultural Psychology*, *44*, 24-45. doi:10.1177/0022022111430255

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models* (2nd ed.). London, England: Sage.

Rost, J., & Langeheine, R. (Eds.). (1997). *Applications of latent trait and latent class models in the social sciences*. Münster, Germany: Waxmann.

Schwartz, S. H. (1992). Universals in the content and structure of values: Theoretical advances and empirical tests in 20 countries. In M. Zanna (Ed.), *Advances in experimental social psychology* (Vol. *25*, pp. 1-65). Orlando, FL: Academic Press.

Searle, S. R., Casella, G., & McCulloch, C. E. (1992). *Variance components*. New York, NY: Wiley.

Snijders, T., & Bosker, R. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed.). Thousand Oaks, CA: Sage.

Triandis, H. C. (1993). Collectivism and individualism as cultural syndromes. *Cross-Cultural Research*, *27*, 155-180.

Triandis, H. C. (1996). The psychological measurement of cultural syndromes. *American Psychologist*, *51*, 407-415.

Triandis, H. C., Leung, K., Villareal, M., & Clark, F. L. (1985). Allocentric vs. idiocentric tendencies: Convergent and discriminant validation. *Journal of Research in Personality*, *19*, 395-415.

van de Vijver, F. J. R., & Leung, K. (1997). *Methods and data analysis for cross-cultural research*. Thousand Oaks, CA: Sage.

van de Vijver, F. J. R., & Leung, K. (2000). Methodological issues in psychological research on culture. *Journal of Cross-Cultural Psychology*, *31*, 33-51.

van de Vijver, F. J. R., van Hemert, D. A., & Poortinga, Y. H. (Eds.). (2008). *Multilevel analysis of individuals and cultures*. New York, NY: Lawrence Erlbaum.

Verbeke, G., & Molenberghs, G. (2000). *Linear mixed models for longitudinal data*. New York, NY: Springer.

Vermunt, J. K. (2002). An expectation-maximization algorithm for generalized linear three-level models. *Multilevel Modelling Newsletter*, *14*, 3-10.

Vermunt, J. K. (2003). Multilevel latent class models. *Sociological Methodology*, *33*, 213-239.

Vermunt, J. K. (2004). An EM algorithm for the estimation of parametric and nonparametric hierarchical nonlinear models. *Statistica Neerlandica*, *58*, 220-233.

Vermunt, J. K., & Magidson, J. (2008). *LG-syntax user's guide: Manual for Latent GOLD 4.5 syntax module*. Belmont, MA: Statistical Innovations.

Vignoles, V., & Brown, R. (2011). *Motivated Identity Construction in Cultural Context, 2008–2011 (Study No. 6877)* [Computer file]. Colchester, Essex: UK Data Archive [Distributor].

Yu, H.-T. (2007). *Multilevel latent Markov models for nested longitudinal discrete data* (Unpublished doctoral dissertation). University of Illinois at Urbana–Champaign.

Yu, H.-T. (2013). Models with discrete latent variables for analysis of categorical data: A framework and a MATLAB MDLV toolbox. *Behavioral Research Methods*, *45*, 1036-1047. doi:10.3758/s13428-013-0335-0