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Modeling unobserved heterogeneity using person-centered approaches: Latent profiles of preservice teachers' emotional awareness

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Abstract: Latent Class and Latent Profile Models are widely used in psychological assessment settings, especially when individual differences are suspected to be related to unobserved class memberships, such as different personality types. This paper provides an easy-to-follow introduction and application of the methodology to the data collected as part of more extensive educational research investigating social-emotional competency profiles of preservice teachers (n=184) who responded to an Emotional Awareness Questionnaire. Suspected that there would be two or more latent emotional awareness sub-groups in the sample, a series of latent profile models was estimated. The results suggested three distinct emotional awareness profiles; namely, introverted, extroverted, and less sensitive to others' emotions, with proportions of 9%, 56%, and 35%, respectively. Subsequent analyses showed that preservice teachers with higher levels of emotionality, sociability, and well-being were more likely to be in the extroverted profile. The findings suggest that nearly half of the teachers in the sample could be expected to possess the most professionally desirable teacher profile. Nonetheless, it was noted that if timely diagnostic and tailored training or intervention programs were available, at least some of the preservice teachers in the less sensitive to others' profiles, and most of the preservice teachers in the introverted profile could be helped to self-observe the way which they tend to identify and regulate their emotions.

1. INTRODUCTION

Individual differences represent an important issue for educators and researchers (Snow, 1986) since individuals of any age and culture differ in various cognitive, affective, and psychomotor skills, which are directly related to differences in individuals' learning and growth processes. To this end, many kinds of research strive to characterize patterns and pathways of individuals' development (Hickendorff et al., 2018). Furthermore, development can occur in stages, growth patterns can vary between individuals, and growth can interact with individuals' characteristics. The development of populations in educational and psychological sciences is often heterogeneous, while population heterogeneity can be observed or unobserved. Heterogeneity

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is observed if it is possible to define the subpopulations based on an observed variable such as gender, control, and experimental groups. In observed heterogeneity, group membership is known for each participant. However, the sources of unobserved heterogeneity may not be known a priori (Lubke & Muthen, 2005) and disregarding the unobserved heterogeneity in investigating individual differences may cause inadequate descriptions for many individuals in a population (Hickendorff et al., 2018). When the subpopulation membership of the participants is not observed, group memberships should be inferred from the data collected. In the context of unobserved heterogeneity, subpopulations are called latent classes or profiles. Therefore, assessing and modeling the heterogeneity is essential for understanding how and under which circumstances growth occurs. In such cases, the researcher may use the latent profile or latent class analyses to model the unobserved heterogeneity between and within individuals more appropriately.

In social, behavioral, and educational sciences, programs are often administered to populations without consideration of individual characteristics. Recently, there has been growing interest in individualizing treatments to administer the right program to the right individuals to maximize the effectiveness of such treatments (Lanza & Rhoades, 2013). In this context, person-centered approaches have become more helpful in investigating unobserved heterogeneity in a population (Jung & Wickrama, 2008). Latent class analysis (LCA) and latent profile analysis (LPA) are person-centered approaches tracing back heterogeneity in a population to some existing but unobserved sub-groups of individuals (Hickendorff et al., 2018). LPA identifies heterogeneity in cross-sectional data by grouping participants into latent classes based on similarities in the continuous observed/indicator variables.

LCA and LPA are in the Finite Mixture Modeling framework (Gibson, 1959; Hickendorff et al., 2018; Peugh & Fan, 2013), referring to a class of statistical analysis techniques designed to model unobserved population heterogeneity by grouping individuals. Mixture models have different names depending on whether the observed and latent variables are continuous or categorical. These models are shown in Table 1, in which the rows correspond to continuous and categorical observed variables and the columns to continuous and categorical latent variables. LPA determines latent groups using continuous observed variables, and LCA does the same using categorical variables (Oberski, 2016).

Table 1. *Latent variable models**

		Latent Variables	
		Categorical	Continuous
Observed Variables	Categorical	Latent Class Analysis	Item Response Theory
	Continuous	Latent Profile Analysis	Factor Analysis

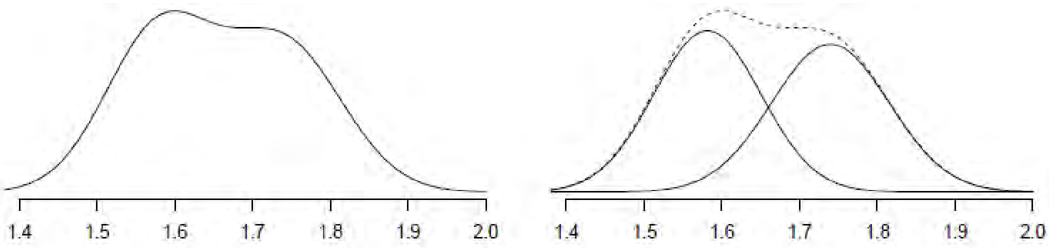
*Muthén, B. (2007). Latent variable hybrids: Overview of old and new methods. In G.R. Hancock & K.M. Samuelsen (Eds.), *Advances in latent variable mixture modeling* (pp. 1-24). Information Age.

LPA models are similar to clustering methods, while they have a more flexible structure (Tein et al., 2013). The primary goal of LPA is to maximize the homogeneity within groups (i.e., individuals within a profile should be similar) and maximize the heterogeneity between groups (i.e., individuals between profiles should be different). These groups are represented by a categorical latent variable, as they are not directly known but inferred from observed variables' response patterns (Roesch et al., 2010). Identifying latent profiles can be useful for characterizing qualitative and quantitative inter-and intra- individual differences simultaneously (Hickendorff et al., 2018).

LPA is a model-based technique that is a version of the traditional cluster analysis. It is similar to *k*-means cluster analysis in that both methods divide individuals into categories based on response patterns (Peugh & Fan, 2013). The objective of *k*-mean cluster analysis is to quantify separation in the multivariate distance as it categorizes individuals based on response similarities that maximize between-category variance and minimizes within-category variance. LPA aims to identify the heterogeneous (k>1) population model that generates the data using maximum likelihood estimation (Steinley & Brusco, 2011). In k-means cluster analysis, an individual either is (1) or is not (0) a member of cluster k. In LPA, latent profile membership is estimated as a probability based on a participant's observed/indicator variable scores (Peugh & Fan, 2013).

In Figure 1, the plots, coming from hypothetical data on height, are given (Oberski, 2016). The height distribution on the left-hand side of Figure 1 is not normal; for example, when two different normal distribution groups (suppose women and men) are combined on the right-hand side, the non-normal distribution picture emerges. When modifications are made for the sub-groups in a sample, we can obtain a picture like a plot on the right. However, the distribution obtained over the total group may not show us the same distribution. Even more commonly, we may need difficult or impossible information to get at directly. LPA is, therefore, concerned with recovering such hidden (latent) groups.

Figure 1. *People's height*[*].



Note: Left: observed distribution. Right: women and men separate, with the total shown as a dotted line.
*Oberski, D. L. (2016). Mixture models: latent profile and latent class analysis. In J. Robertson, & M. Kaptein (Eds.), *Modern statistical methods for HCI* (pp. 275-287). Springer International.

The LPA is beneficial in examining situations where there is doubt that a defined model does not apply to all individuals. In cases where there are many variables, and there is a need to reduce them to interpretable groups, techniques such as LPA can be used to construct a meaningful relationship between variables and interpret those relations. LPA divides the observations into mutually exclusive groups when the observed variables are unrelated to each other within each class (independent), and instead of assuming that the variables come from any specific distribution, LPA allows them to follow any distribution as long as they are independent within classes (Oberski, 2016). In summary, LPA offers a parsimonious way to classify latent profiles using theoretically reasonable and particular variables (Stanley et al., 2017). LPA can also examine the relationships between class membership and external variables not used in the model (Oberski, 2016).

Variable-centered approaches that assume homogeneity in the nature of individual differences (Hickendorff et al., 2018) emphasize the relations between variables and accept that all individuals belong to the same population or come from known groups such as gender and ethnicity. On the other hand, person-centered approaches that focus on the relationships among individuals aim to group individuals into sub-groups, each containing individuals similar to each other and different from individuals in other groups (Muthén & Muthén, 2000). LPA (person-centered approach) and factor analysis (variable-centered approach) can be compared to understand LPA better. While the main purpose of the former is to find groups of individuals who are similar by using continuous observed variables, the aim of the latter is to find the smallest number of dimensions that can explain the relationships among a set of observed continuous variables (Muthén & Muthén, 2000). The difference is that factor analysis separates the covariances to show the relationships among variables, whereas LPA separates the covariances to show the relationships among individuals (Ferguson et al., 2020).

It can be seen that the use of LPA has increased considerably by applied researchers in the educational and social sciences in recent years (Ferguson et al., 2020). LPA is frequently used in modeling latent profiles/classes related to psychological structures (Bouckenooghe et al., 2019; Ferguson & Hull, 2019; Kim & Lee, 2021; Kökçam et al., 2022; Merz & Roesch, 2011; Wang et al., 2019; Wei et al., 2021; Yalçın et al., 2022) and in defining latent profile characteristics and examining the properties of those profiles in other fields (Bondjers et al., 2018; Grunschel et al., 2013; Lehmann et al., 2019; Saritepeci et al., 2022; Stanley et al., 2017; Wade et al., 2006; Williams et al., 2016).

This current study presents a brief introduction and application of LPA for researchers interested in exploring unobserved heterogeneity and integrating this type of analysis into their research, providing a helpful guide to LPA's model requirements and reporting practices, and focusing on the practical points in the analysis, proposes approaches supported by the current methodology research, and directs the researchers to additional resources for further investigation. The present application used LPA to determine the qualitatively different emotional awareness sub-groups of preservice teachers by using Emotional Awareness Questionnaire (EAQ; Rieffe et al., 2008) data. Also, covariates were integrated into the model to explore the relationships and differences between profiles (Nylund-Gibson & Masyn, 2016) by taking the Trait Emotional Intelligence Questionnaire (TEIQ; Petrides & Furnham, 2000) scores.

Emotional competence has become prominent in educational sciences, psychology, and other fields (Ashkanasy & Dasborough, 2013; Ulloa et al., 2016) as emotional competence is a fundamental part of people's social development and identifies their ability to interact and create relationships with others (Ulloa et al., 2016). Substantial evidence shows that the way of teachers' interaction with children affects their social and emotional attitudes, while emotional competencies of teachers, like emotional awareness, play a valuable role in developing positive relationships with children and contribute to forming a healthy climate in classrooms (Gottman & Declaire, 1997; Harvey & Evans, 2003; McCarthy, 2021). Therefore, teachers' emotional competencies should be supported to meet children's emotional needs. The method presented here can be used to understand teachers' emotional awareness profiles, enrich our inferences, and enhance teachers' emotional competencies.

This study, therefore, aims to demonstrate the LPA process using emotional awareness data to identify unobserved heterogeneity in a sample, identify whether emotional awareness profiles exist among preservice teachers, and evaluate predictors of profile membership. To this end, the research questions are as follows:

1) How many latent profiles exist in the EAQ data?
2) Do TEIQ scores (as covariates) predict latent profile membership?

2. METHOD

2.1. Study Group

The data came from a larger prospective research project and were used here only for illustrative purposes to demonstrate LPA, as opposed to the theoretical implications of the results. The data were collected from 184 volunteer preservice teachers in the fall and spring terms of the 2020-2021 academic year. The study group comprised 76% female and 14% male preservice teachers, and their mean age was 21.

The required sample size in LPA depends on the number of profiles and the distance between the profiles, but these are generally unknown and can only be estimated based on prior research

(Tein et al., 2013). However, there is currently no simple formula or calculator to estimate the required sample. Wurpts and Geiser (2014) suggested that sample sizes are well into the hundreds, and samples below n=70 are not suitable under virtually any circumstances. In this study, it is assumed that the sample size is feasible for LPA.

2.2. Data Collection Tools

Emotional Awareness Questionnaire (EAQ; Rieffe et al., 2008) aims to identify how people feel and think about their feelings. The present EAQ (30 items) was designed with a six-factor structure describing six aspects of emotional functioning; namely, (1) differentiating emotions, (2) verbal sharing of emotions, (3) not hiding emotions (formerly acting out), (4) bodily awareness of emotions, (5) attending to others' emotions, and (6) analyses of emotions. The respondents were asked to rate the degree to which each item was proper for them on a 5-point scale (*from 1 = not true to 5 = true*).

Scale items were translated into Turkish by the researchers, and Exploratory Factor Analysis (EFA) was conducted to examine the factor structure of the adapted version. According to the results of EFA, a Kaiser-Meyer-Olkin (KMO) value was found to be 0.81. Chi-square (χ^2) statistic and the result of Bartlett's test were statistically significant (χ^2 (435) = 2372.97, p < .05). The data were found to have a six-factor structure with eigenvalues between 1.01 and 5.87, and the total variance explained by the factors was 49.89%. Cronbach α reliability coefficient was calculated for each sub-factor and found as 0.82, 0.71, 0.74, 0.82, 0.82, and 0.81.

Trait Emotional Intelligence Questionnaire (TEIQ; Petrides & Furnham, 2000) scores were added as covariates to the LPA model. Turkish version of TEIQ (Deniz et al., 2013) was used to measure the level of self-perception of an individual's emotional competencies. Emotional intelligence can be assessed under such four sub-factors in TEIQ as 1) emotionality, 2) well-being, 3) social, and 4) self-control. Each factor is measured by four items. Items can be responded to on a 7-point scale, ranging from "applies to me very well" (7 points) to "does not apply to me at all" (1 point). Values for each factor vary between 4 and 28. In this study, the Cronbach α reliability coefficient for each sub-factor was calculated as 0.50, 0.73, 0.64, and 0.48.

2.3. Data Analysis

2.3.1. *Latent profile analysis*

LPA (Lanza et al., 2003) is a technique for discovering latent groups in data by acquiring the probability of individuals regarding different groups. LPA thoroughly investigates the distributions of groups in the sample and determines whether those distributions are substantial or not. It might be helpful to consider if these groups are profiles of individuals as observed latent mixture components or not (Ferguson & Hull, 2019).

In LPA, the researcher works through an iterative modeling process to define the number of profiles and fits a covariate model to explore the effect of these profiles on other variables or to estimate profile membership (Bauer & Curran, 2004; Sterba, 2013). The object of LPA is to discover latent profiles (k) of individuals (i) who share a meaningful and interpretable pattern of responses on the measures of interest (j) (Marsh et al., 2009; Masyn, 2013). The joint and marginal probabilities in within-class and between-class models are used to estimate latent profiles. Within-class model is defined by two equations (Ferguson et al., 2020) as follows:

$$y_{ij} = \mu_j^{(k)} + \varepsilon_{ij} \tag{1}$$

$$\varepsilon_{ij} \sim N\left(0, \sigma_j^{2\,(k)}\right) \tag{2}$$

where $\mu_j^{(k)}$ is the model denoted mean and $\sigma_j^{2\,(k)}$ is the model denoted variance, which will vary across $j = 1 \ldots J$ outcomes and $k = 1 \ldots K$ classes or profiles, and ε_{ij} denoted the error term. The general assumption of LPA implies that outcome variables are normally distributed and locally independent* within each class (Sterba, 2013). The between-class model represents the probability of membership in a given class k:

$$p(c_i = k) = \exp(\omega^{(k)}) / \textstyle\sum_{k=1}^{K} \exp(\omega(k)) \tag{3}$$

where $\omega^{(k)}$ is a multinomial intercept and c_i is the latent classification variable for the individual. The within-class and between-class models can therefore be combined into a single model using total probability resulting in

$$f(y_i) = \textstyle\sum_{k=1}^{K} p(ci = k) f(y_i \mid c_i = k) \tag{4}$$

which is the marginal probability density function for an individual (i) after summing across the joint within-class density probabilities for the J outcome variables, weighted by the probability of class or profile membership from equation (3). Finally, LPA results in a posterior probability for each individual are defined as

$$t_{ik} = p(c_i = k \mid \boldsymbol{y}_i) = \frac{p(ci = k) f(yi \mid ci = k)}{fyi} \tag{5}$$

representing the probability of an individual (i) being assigned membership (c_i) in a specific class or profile (k) given their scores on the outcome variables in the y_i vector. A posterior probability (t) is calculated for each individual in each profile, with values closer to 1.0 indicating a higher probability of membership in a specific profile. The more distinctions between an individual's posterior probabilities, the more certainty there is around their membership assignment (Sterba, 2013).

In general, as the number of indicators and/or latent profiles/classes increases, the number of parameters to be estimated increases; especially the number of free parameters associated with variances and covariances increases. For more parsimonious models, researchers assume that the class-specific covariance matrix is diagonal (i.e., all within-cluster covariances are equal to zero), which forces a constraint of homogeneity of variances across latent profiles. The result of these constraints is that all the latent profiles have the same form of distribution, differing only in their means (Tein et al., 2013).

2.3.2. *Steps of LPA*

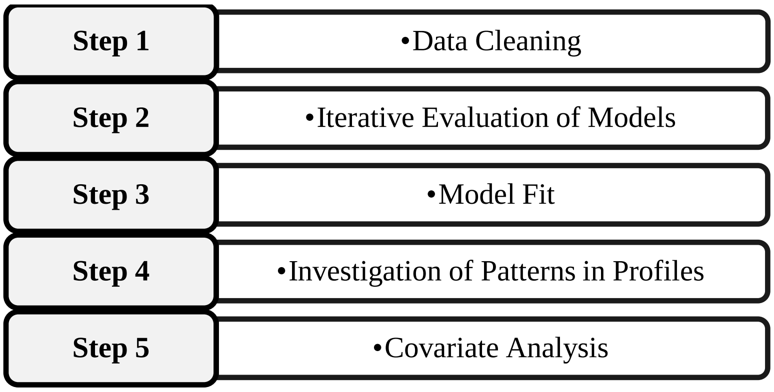
The analysis has five common steps (shown in Figure 2) as defined by Ferguson et al. (2020). *Step 1* involves data cleaning for analysis and checking for standard statistical assumptions. In the present application of LPA, the data did not contain missing values because those participants who had a missing value on one of the scales were removed from the data. However, if the data has missing values, it can be handled by full-information maximum likelihood (FIML) or multiple imputations, depending on what is best for the data (Ferguson & Hull, 2019).

Step 2 involves assessing a series of hypothetically plausible iterative LPA models, starting with one profile, and ending with the best fit of the model to the data (Hickendorff et al., 2018). Model 1 was estimated with only one profile, Model 2 with two profiles, Model 3 with three profiles, and Model 4 with four profiles to determine the best-fitting model for the data. LPA

* Local independence is a default assumption in many latent variable models but can be relaxed (Bauer, 2022). M*plus* program, by default, also imposes local independence and homogeneity across classes.

was conducted using M*plus* (8.3 version) (Muthén & Muthén, 1998-2017) with maximum likelihood estimation with robust standard errors (MLR).

Figure 2. *Five steps of Latent Profile Analysis*.*



* Ferguson, S. L., Moore, E. W., & Hull, D. M. (2020). Finding latent groups in observed data: A primer on latent profile analysis in Mplus for applied researchers. *International Journal of Behavioral Development, 44*(5), 458-468. https://doi.org/10.1177/0165025419881721

Step 3 involves assessing models to define model fit and interpretability. One of the essential works in LPA is accurately describing the number of underlying latent profiles and correctly placing individuals into their profiles with high precision. Appropriately selecting the correct number of latent profiles is crucial because the number of profiles chosen can have a powerful impact on substantive interpretations of the results (Tein et al., 2013). Selecting the number of profiles typically involves estimating models with incremental numbers of latent profiles (e.g., 2, 3, and 4 latent classes) and choosing the number of profiles based on which model best fits the observed data. The model selection process is probably the most prominent and challenging issue. Most common methods for deciding the number of profiles fall into three categories: information criterion methods, likelihood ratio statistical test methods, and the entropy index (Nylund et al., 2007; Tein et al., 2013).

The first category, information-theoretic methods, involves Akaike's Information Criterion (AIC; Akaike, 1987) and Bayesian Information Criterion (BIC; Schwarz, 1978), which are the most commonly used indices. The AIC and BIC are based on the maximum likelihood estimates of the model parameters for deciding the most parsimonious and correct model. AIC and BIC are used for model selection, with lower values representing the retained model (Masyn, 2013).

The second category involves likelihood ratio statistic tests (LRTs) that compare the relative fit of two models that differ by a set of parameter restrictions (Tein et al., 2013). To illustrate, Lo, Mendell, and Rubin (LMR-LRT) is used to compare models in a similar context to the χ^2 difference test in other model testing analyses (Lo et al., 2001); LMR-LRT evaluates significance across differences in degrees of freedom and helps determine when additional profiles are not improving the fit or discrimination of the model. Thus, a nonsignificant LMR-LRT suggests that the more parsimonious model fits better (Ferguson & Hull, 2019). The bootstrap likelihood ratio test (BLRT) and Vuong-Lo-Mendell-Rubin (VLMR-LRT) can be used to compare the fit of one model (k) compared to a model with one less class (k-1). BLRT uses parameter estimation methods to create multiple bootstrap samples representing the sampling distribution (Masyn, 2013). A statistically significant BLRT indicates that the current model fits better than a model with a k-1 class. For LMR-LRT, VLMR-LRT, and BLRT, a small probability value (e.g., $p < .05$) indicates that the k-class model provides a significantly better fit to the observed data than the $k-1$ class model does (Whittaker & Miller, 2021).

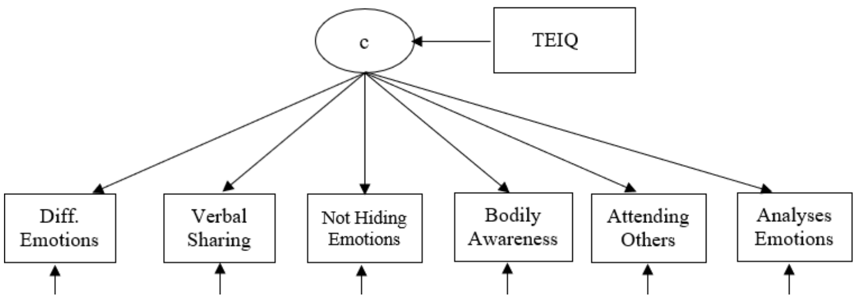
The third category is the measure of entropy. The entropy index is based on the uncertainty of classification (Celeux & Soromenho, 1996), while the entropy index scales to the interval (0, 1). A higher value of entropy represents a better fit; values > 0.80 indicate that the latent profiles are highly discriminating (Tein et al., 2013).

In addition to model fit indices, evaluating the reasonableness of an LPA model is necessary to provide the final model and underlying profiles that represent interpretable and meaningful groupings of individuals. Profiles containing less than 5% of the sample may be spurious, and the relevance of such profiles should be carefully considered and examined for interpretability (Marsh et al., 2009).

Step 4 involves interpreting the retained model by examining patterns of the profiles and weights of variables included in each profile. The means and standard deviations of variables used to create the profiles are conditioned and presented for each profile. It may help report LPA to provide names for the profiles based on the observed differences in indicator variables. Correct naming of profiles provides accuracy and clarity in generalizing and interpreting results (Ferguson & Hull, 2019).

Step 5 involves conducting a covariate analysis. This step should be included when (a) LPA analysis indicates that there are profiles worth interpreting further and (b) there is a theoretical reason to evaluate the impact of the covariates on the profiles (Ferguson & Hull, 2019). Examining relationships with covariates provides additional information on the latent profiles and how the covariate variables may have differing effects on these profiles. A three-step approach (Vermunt, 2010) is used for the inclusion of covariates in the LPA. The first step of the three-step approach is determining the number of latent profiles without including the covariates in the model (Marsh et al., 2009); in the second step, the individuals' class probabilities are used to specify their membership probability into each latent profile; and in the third step, the logit values for the most likely class are regressed on covariate variables, considering the misclassification in the second step (Asparouhov & Muthen, 2014). Using the three-step approach means that indicators for the profiles are present in the model with the covariates during data analysis, as shown in Figure 3.

Figure 3. *LPA model with covariate.*



Note. TEIQ=Emotional intelligence scores; Diff. Emotions=Differentiating Emotions.
Differentiating emotions, verbal sharing, not hiding emotions, bodily awareness, attending to others, and analyses of emotions are observed/indicators of emotional awareness.

Figure 3 shows the observed/indicator and covariate variables for the EAQ construct. TEIQ scores were added by regressing the latent profile membership into the model as a covariate of latent class *c* in Figure 3. In this study, first, basic LPA models were tested and examined to identify the presence of latent profiles of emotional awareness (research question 1), and then, LPA models with covariates were tested and examined to evaluate the effects of covariates for defining latent profiles (research question 2).

3. RESULTS

LPA results are given in accordance with the steps followed, and the research questions asked. In Step 1, the data were cleaned, and participants were removed from the analysis if values on all variables in the study were missing. Therefore, the results involve LPA steps from two to five.

3.1. Results of Research Question-1

Research question 1 involves results from the second to the fourth step of LPA. In Step 2, a series of LPA models were evaluated, starting with one profile (Model 1) and ending with a model with four profiles (Model 4).

Step 3 involves evaluating model fit to identify latent profiles. Model 3 was retained as the best-fitting model to the data based on the lower AIC and BIC values, high entropy, and the significant LMR-LRT, while the smallest class contained more than 5% of the sample (Table 2). BIC was marginally lower for Model 3 compared to Model 4. The entropy for Model 3 was 0.77. The LMR-LRT, VLMR-LRT, and BLRT tests were significant for Model 3, which means the three-profile model is better than the two-profile model. These results showed that adding new classes to the model, from the one-class to the three-class model, improves the model-data fit. However, adding a class to the three-profile model did not improve the model-data fit because LMR-LRT was not significant for Model 4, which means the more parsimonious Model 3 had a better fit than that of the less parsimonious model. The smallest profile in Model 3 comprised 9% (*n*=17) of the sample. It was therefore concluded that the three-profile model better fits the data under the interpretability and parsimonious principle.

Table 2. *Model fit summary of LPA models.*

Model Fit Statistics	Model 1	Model 2	Model 3*	Model 4
AIC	6047.74	5945.87	5907.27	5898.07
BIC	6086.32	6006.95	5990.86	6004.16
Entropy	*	0.67	0.77	0.70
Smallest class %	*	49	9	8
LMR-LRT p-value	*	0.00	0.02	0.84
VLMR-LRT p-value	*	0.00	0.02	0.83
BLRT p-value	*	0.00	0.00	0.06

Note. *n*=184; *p*-value < .05 *Retained model for the emotional awareness data

In Step 4, the retained model was interpreted by examining the patterns of the latent profiles. As the results of the three-profile model are given in Table 3, it can be seen that the standardized means used to create the classes were presented for each profile, and all were found to be statistically significant. *Profile 1* contained preservice teachers with the lowest level of differentiating emotions, verbal sharing, not hiding emotions, and bodily awareness (lower values indicate that more bodily symptoms accompany emotions), which was referred to as "Introverted". *Profile 2* contained preservice teachers with the mid-level of differentiating emotions, verbal sharing, not hiding emotions, the highest level of bodily awareness, the lowest level of attending to others, and analyses emotions, so it was referred to as "Less Sensitive to Others' Emotions". *Profile 3* contained preservice teachers with the highest level of differentiating emotions, verbal sharing, not hiding emotions, the mid-level of bodily awareness, the highest level of attending to others, and analyses of emotions, so it was referred to as "Extroverted".

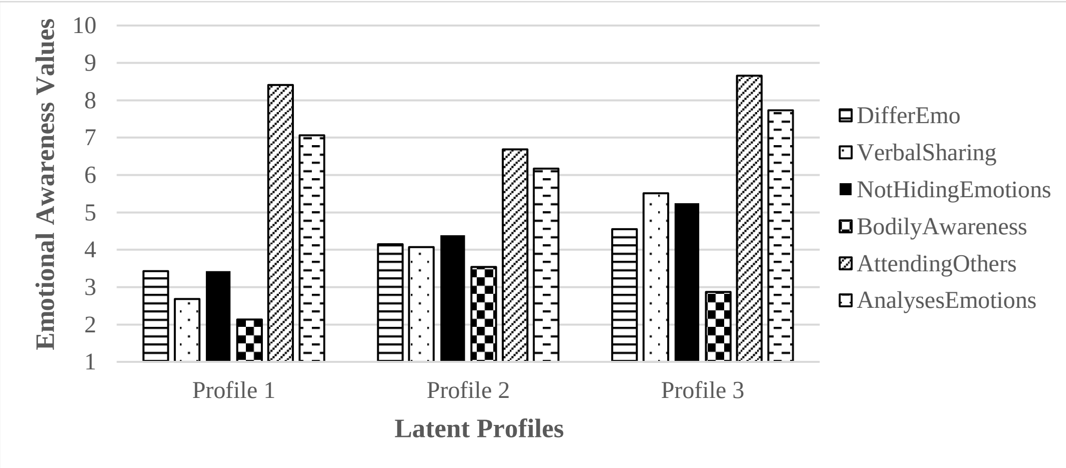
Additionally, the classification uncertainty value entropy was calculated as 0.77. This result shows that the retained three-profile model was effective in assigning individuals to the correct latent profiles. The latent profile membership of each participant was calculated based on the posterior class probabilities, which represent the probability of being in each of the *k* latent classes based on observed responses to the items. It was seen that classification probabilities in the three-profile model were 0.80 or greater (0.80, 0.88, 0.95), indicating that participants were assigned to corresponding latent profiles with high probabilities. This result supported the usefulness of the three-profile model in assigning individuals to the correct classes.

Table 3. *Mean values of observed variables for three-profiles model.*

Indicator Variables	Profile 1	Profile 2	Profile 3
Differentiating Emotions	3.43	4.14	4.55
Verbal Sharing	2.68	4.07	5.50
Not Hiding Emotions	3.42	4.38	5.24
Bodily Awareness	2.12	3.54	2.87
Attending to Others	8.40	6.68	8.65
Analyses Emotions	7.05	6.17	7.73
Class Proportions	9% (*n* = 17)	35% (*n* = 65)	56% (*n* = 102)

Figure 4 involved plots for comparing profiles on indicator variables. While *Profiles 1* and *3* contained preservice teachers with high scores in attending to others and analyses emotions, *Profile* 2 contained preservice teachers with lower scores in attending to others, analyses emotions, and higher scores in bodily awareness compared to those of other profiles.

Figure 4. *Histograms for latent profiles.*



Note. Profile 1=Introverted, Profile 2= Less sensitive to others' emotions, Profile 3= Extroverted DifferEmo: differentiating emotions, VerbalSharing: verbal sharing of emotions, NotHidingEmotions: not hiding emotions (formerly acting out), BodilyAwareness: bodily awareness of emotions, AttendingOthers: attending to others' emotions, and AnalysesEmotions: analyses of emotions.

3.2. Results of Research Question-2

Research question 2 involves the results of covariate analysis (Step 5). TEIQ scores were added to the model by regressing the latent profile. *Profile 3* (Extroverted) was used as the reference group for model comparisons.

Odds ratios were computed to evaluate differences in the likelihood of profile membership based on covariate scores. TEIQ sub-factors were emotionality, well-being, sociability, and self-control. Odds ratios demonstrating the likelihood of profile membership based on covariate compared to *Profile 3* (Extroverted) are presented in Table 4. Some of the TEIQ sub-factors produced significant differences across profiles ($p < .05$). Positive coefficients indicated that the probability of participants with high related TEIQ sub-factor scores tends to be other profiles as compared to the reference profile (*Profile 3 - Extroverted).* Regarding the significant and negative coefficients, it could be implied that participants with high levels of emotionality and well-being were less likely to be in *Profile 1 (Introverted)* and *Profile 2 (Less sensitive to others' emotions)* compared to the reference profile. Besides, participants with high sociability values were less likely to be in *Profile 2* relative to *Profile 3;* however, the self-control sub-factor had no significant effect.

Table 4. *Covariate analysis results for the three-profile model.*

Covariate Variables	Latent Profiles	
	Profile 1 (slope/odds ratio) Introverted	Profile 2 (slope/odds ratio) Less sensitive to others' emotions
Emotionality	-0.16 / 0.85*	-0.25 / 0.78*
Well-being	-0.21 / 0.81*	-0.15 / 0.86*
Sociability	-0.15 / 0.86	-0.15 / 0.86*
Self-control	0.04 / 1.04	0.03 / 1.03

Note. *p < .05; Reference class= Profile 3 (Extroverted)

4. DISCUSSION and CONCLUSION

In this paper, we provide an overview of LPA and highlight the strengths of this analytic approach, which is a member of latent variable mixture models and uses continuous data collected from cross-sectional measurement points (Berlin et al., 2014). A step-by-step LPA guide was provided illustrating the methodology which was used to determine the number of meaningful latent classes and their patterns to advance our understanding of preservice teachers' capabilities in relation to emotional awareness.

Collected as a part of a larger research project focusing on social and emotional competencies of preservice teachers, emotional awareness data were used 1) to predict the latent profile construct underlying the data and to test if some of the profile differences could be explained by the emotionality, well-being, sociability, and self-control as covariates, and 2) to interpret the resulting emotional awareness profiles as they pertained to the desired qualifications in the teaching profession. The results showed that, based on their EAQ scores, preservice teachers could be classified into three distinct profiles, namely Introverted (9%), Less Sensitive to Others' Emotions (35%), and Extroverted (56%), suggesting that there were sub-groups of preservice teachers having distinct characteristics and needs. According to the results, only up to half of the teachers in the sample were identified as having the professionally desired emotional awareness levels. Furthermore, some of the TEIQ sub-factors that were tested as covariates were found to play an important role in profile memberships. For example, it was found that preservice teachers with higher well-being and emotionality self-ratings were less likely to be introverted and less sensitive to others' profiles compared to extroverted profile. Overall, our findings indicate that we need to consider the added value of utilizing theoretically meaningful hypotheses and covariate variables in order to investigate the profile patterns of teachers in a detailed way.

The present study also highlights the importance of recovering hidden sub-groups within the sample of preservice teachers. LPA can be beneficial, especially for gaining a better understanding of the characteristics of the target populations. Teachers with higher social and emotional capabilities are expected to show more awareness about their own emotions, discriminate between their feelings and those of others, monitor and regulate their internal processes, and understand more accurately the causes of emotions in themselves and the children they work with in comparison to those with little social or non-emotionally capabilities (Jennings & Greenberg, 2009). Because of these capabilities, emotionally aware teachers are expected to implement positive strategies and cultivate self-awareness skills to understand and reflect on the emotional difficulties that underlie children's behavior (Ulloa et al., 2016) since developing emotional awareness competencies has been reported to reduce inappropriate behaviors in the classroom, reduce stress, and improve achievement (McCarthy, 2021).

Although only several teacher certification programs to date are known to emphasize social-emotional competencies in their list of priority competencies (McCarthy, 2021), many studies recognize the importance of integrating social-emotional skills into teacher education programs (Ulloa et al., 2016). Our results confirm that preservice teachers differ qualitatively concerning their emotional awareness capabilities, and also enhancing teacher training programs to diagnose their social and emotional capabilities can set the basis for designing or modifying coursework and other activities serving the needs of those in different stages of their social-emotional development. Our results, therefore, indicate that some preservice teachers appear to be in the less-than-ideal emotional awareness profiles and could use the help of additional training programs and other aids.

Some limitations need to be noted regarding the present study. This study is limited to university students, which may have affected the generalizability of the results. In addition, emotional intelligence sub-factor scores were considered for the classification of emotional awareness profiles, and due to this, understanding of memberships of emotional awareness groups may have remained limited. Since this research was exploratory, it is necessary to examine its validity through confirmatory analyses in future studies. Evaluation of item and scale parameter estimates can also inform other researchers, especially when making inferences about the potential use of alternative model covariates, for there could be different effects across different latent classes (Whittaker & Miller, 2021). For instance, the effects of covariates on class membership might improve model performance in terms of a correct class assignment (Lubke & Muthen, 2005). Although greatly useful as a methodology, researchers are recommended to formulate LPA models using theoretically meaningful latent class constructs and covariates to the extent possible.

This paper uses LPA to diagnose and describe preservice teachers' latent profile differences concerning their emotional awareness levels and social-emotional skills in general. Also, it illustrates that adding predictor variables as covariates to the LPA models may help discover relationships and other inherent differences between latent groups (Bouckenooghe et al., 2019; Hill et al., 2006; Nylund-Gibson & Masyn, 2016; Stanley et al., 2017). By utilizing LPA, detailed information can be obtained about qualitative individual differences related to the particular construct of interests to further understand preservice teachers' characteristics and determine their strengths and weaknesses. Thus, through timely diagnostics and proper curricula or program improvement targeting specific needs and skills, existing teacher training programs can be updated to empower future teachers.

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Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The studies involving human participants are reviewed and approved by the Gazi University Ethics Committee (Ethics Committee Number: 77082166-604.01.02).

Authorship Contribution Statement

Esra Sozer-Boz: Investigation, Resources, Data Collection, Visualization, Software, Methodology, and Writing-original draft. **Derya Akbas**: Investigation, Data Collection, Methodology, Software, and Validation. **Nilufer Kahraman**: Supervision and Validation.

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