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Applying latent profile analysis in foreign language anxiety research: Uncovering hidden groups

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Abstract

To gain a deeper understanding of the complexity of foreign language anxiety (FLA), researchers have leveraged various quantitative and qualitative methods. Considering quantitative methods, researchers have mostly used variable-centered approaches to examine the relationships between FLA and other variables. However, less attention has been given to person-centered approaches, which aim to identify subgroups of a population to better understand individual differences and heterogeneity. This study applies latent profile analysis (LPA), a robust person-centered method, to uncover FLA profiles and to examine the predictors and outcomes of FLA profiles. To this aim, we first reviewed person-centered methods, addressing best practices and methodological considerations for conducting LPA. For the empirical study, we gathered data from 384 tertiary-level EFL learners using a questionnaire, which measured their FLA, achievement goals, and willingness to communicate. The LPA results revealed five distinct latent profiles of FLA, characterized not only by the intensity of anxiety but also by its manifestations and triggers. Each profile also showed meaningful differences in achievement goals and willingness to communicate.

By applying LPA, we were able to gain a deeper understanding of how FLA is experienced across different learner subgroups. We believe that person-centered approaches, such as LPA, provide additional value in investigating anxiety and other emotions in language education research.

Keywords: foreign language anxiety; latent profile analysis; latent class analysis; person-centered approaches; achievement goals

1. Introduction

Foreign language anxiety (FLA) is the most extensively researched emotional construct in the field of second/foreign language (L2) learning (MacIntyre, 2017; Papi & Khajavy, 2023). It is defined as "a distinct complex of self-perceptions, beliefs, feelings, and behaviors related to classroom language learning arising from the uniqueness of the language learning process" (Horwitz et al., 1986, p. 128). Previous research has found that FLA is mostly negatively linked to different language learning outcomes, such as L2 achievement (Botes et al., 2020; Teimouri et al., 2019), willingness to communicate (Khajavy et al., 2018; Li et al., 2025; MacIntyre & Gregersen, 2022), and processes such as cognitive processing (MacIntyre & Gardner, 1994). More specifically, several meta-analytic studies have reported that FLA has moderate correlations with foreign language achievement, highlighting the importance of addressing FLA in the language learning process (e.g., r = -.39 in Botes et al., 2020; r = -.36 in Teimouri et al., 2019; r = -.34 in Zhang, 2019).

More recent research has found that FLA is a complex emotion which is combined with a range of interrelated factors that influence L2 learning (MacIntyre, 2017). To capture the multitude of factors within FLA, researchers need to use more advanced research methodologies, including advanced statistical techniques and increased methodological rigor (Plonsky, 2013, 2015). By reviewing past research on FLA, it becomes clear that the majority of these studies have used variable-centered methods to investigate how different types of FLA are related to other constructs, while less attention has been paid to person-centered approaches. The purpose of person-centered approaches is to identify subgroups to better understand heterogeneity within a population, which can offer insights into understanding learners' and teachers' diverse experiences. Therefore, person-centered approaches can complement variable-centered approaches to provide more detailed insights into FLA. This is because variable-centered approaches can be used to examine how FLA relates to other variables, while person-centered approaches can complement this perspective by uncovering subgroups of learners and showing that relationships among variables might be different across individuals. For instance, a variable-centered analysis (e.g., correlation) might show that higher FLA is related to lower enjoyment and poorer L2 achievement. However, a person-centered approach could indicate that not all anxious L2 learners are similar. A possible scenario is that one group has low FLA and low enjoyment, another group has high FLA and low enjoyment, and a third group has both high FLA and high enjoyment. Moreover, these three groups might be different in their L2 achievement. Considering this, the purpose of the present study is to apply latent profile analysis (LPA) as a powerful person-centered method for understanding FLA and other emotions in second language research. In what follows, we first provide a short review of person-centered approaches and steps for conducting LPA and then review previous studies that have used person-centered approaches to examine FLA. Finally, we use empirical data to illustrate how LPA can be used for FLA research.

2. Review of the literature

2.1. Person-centered and variable-centered approaches

There are generally two major approaches to quantitative data analysis: variable-centered and person-centered approaches (Howard & Hoffman, 2018; von Eye & Spiel, 2010). Variable-centered approaches focus on examining the interrelationships between constructs in a population (e.g., the correlation between L2 anxiety and willingness to communicate, or WTC). These approaches include statistical procedures such as correlation, regression, *t*-test, and structural equation modeling (Wang et al., 2013). Variable-centered approaches assume that the relationships between constructs are the same for all individuals in the population, treating the population as homogeneous (Hickendorff et al., 2018). Although the data may be purposefully divided into subgroups or may rely on moderation analysis (e.g., examining how the role of language anxiety differs depending on gender), this variable-centered method does not consider the complex interactions and individual variability inherent within the data. This is considered a major limitation of variable-centered approaches by not controlling the inherent heterogeneity in the data (Hickendorff et al., 2018).

On the other hand, person-centered approaches account for heterogeneity in the data and recognize the fact that the sample may consist of several subgroups, each with unique parameter sets (Morin et al., 2018, p. 804). Therefore, person-centered approaches can be applied to answer questions about what subpopulations exist within a sample based on a group of variables and how these subpopulations are related to predictors and outcomes (Howard & Hoffman, 2018). According to Hickendorff et al. (2018), what makes person-centered approaches strong is that they take these diverse patterns into account by classifying learners into homogeneous subgroups that share similar characteristics. Examples of person-centered approaches are cluster analysis, latent profile analysis, latent class analysis, and growth mixture modeling.

Research has also distinguished between two major types of person-centered methods: (1) algorithmic approaches involving clustering techniques and (2) latent-variable methods such as LPA (Woo et al., 2018). Two major clustering techniques are k-means and hierarchical clustering which have been already used in L2 research (see Crowther et al., 2021; Staples & Biber, 2015, for a methodological review). Although cluster analysis is a popular statistical technique in other fields of study, such as education (Huberty et al., 2005) and organizational research (Woo et al., 2018), it is not commonly used in L2 research (Plonsky, 2013; Staples and Biber, 2015) and very few studies have used it for examining L2 anxiety or other L2 emotions (Csizér et al., 2024; Papi & Teimouri, 2014; Piniel & Csizér, 2015; Tsang & Yeung, 2024). According to Woo et al. (2018), k-means and hierarchical clustering techniques are favored because the former is easy to run and interpret and can be used for different objectives, while the latter provides a visual display of various clustering options, which helps researchers determine the most suitable cluster arrangement. The second group of person-centered approaches is constituted by latent variable approaches that consider group membership as a latent variable (Woo et al., 2018). When group membership cannot be easily identified by observed subpopulations such as gender and proficiency levels, latent group membership should be identified using latent variable approaches such as latent class and latent profile analysis (Wang et al., 2013). Moreover, they are model-based, referring to a statistical model of the data that is proposed and the probability of each person belonging to a latent group is estimated (Wang et al., 2013; Woo et al., 2018). Considering this, latent variable approaches provide several advantages compared to clustering techniques, such as testing different models using fit indices, examining longitudinal data, and accounting for measurement error (Hickendorff et al., 2018; Marsh et al., 2009; Woo et al., 2018).

When it comes to research on FLA, researchers usually consider their population to be homogeneous and rely on variable-centered approaches such as correlation and SEM to investigate the relationships between FLA and other constructs. However, it is feasible that the population is not homogeneous, a situation that variable-centered approaches cannot adequately address. For example, it is possible that within a single sample of foreign language learners in a study, several distinct groups of language learners may emerge based on their proficiency levels, sociodemographic variables, and FLA. This means researchers need to account for heterogeneity within their samples to provide a more nuanced analysis of their variables. This issue can be addressed by person-centered approaches such as LPA and LCA, which are explained below.

2.2. Latent profile analysis (LPA) and latent class analysis (LCA)

When the goal of a study is to investigate heterogeneity in a population by categorizing individuals into unobserved subpopulations, latent variable approaches can be used (Hickendorff et al., 2018; Wang et al., 2013). The primary goal is to classify individuals into latent groups that are mutually distinct, with each group comprising individuals who share similar characteristics (Marsh et al., 2009). The major latent variable approaches include latent profile analysis, latent class analysis, and latent transition analysis (LTA). These analyses are conducted on observed variables including categorical, continuous, or both. LPA is used with continuous variables, while LCA is applied to categorical variables. It should be noted that some statistical software, such as Mplus, can handle both types of data simultaneously (Bauer, 2022; Hickendorff et al., 2018). In both cases, categorical latent variables represent unobserved subpopulations based on a set of observed variables (Wang et al., 2013). Moreover, when researchers are interested in studying changes in latent groups over time, LTA is used (Woo et al., 2018). Therefore, latent class and latent profile analysis are more appropriate for handling cross-sectional data, and LTA is used for dealing with longitudinal data.

Another characteristic of these models is that they can be used for both exploratory and confirmatory purposes (Bauer, 2022). For the current study, we mainly focus on LPA and LCA as approaches to cross-sectional data analysis, and discussing LTA (see Nylund-Gibson et al., 2023), which requires longitudinal data, is beyond the scope of the current research. When researchers have little knowledge about the characteristics of the latent classes, the approach would be primarily exploratory, while having more knowledge about the nature of the latent classes would be considered a more confirmatory approach (Bauer, 2022; Morin et al., 2018).

2.2.1. Methodological considerations in LPA or LCA

Conducting LPA or LCA requires some methodological considerations and steps to be sure that the analysis has been done and interpreted correctly. Regarding methodological considerations, researchers should consider sample size, variable type (categorical data: LPA/LCA or continuous data: LTA), number of measurement points, and the handling of missing data. First, for sample size, LPA/LCA requires large sample sizes > 500 or at least 200 (Howard & Hoffman, 2018). However, when sample size is small (< 300), authors are recommended to use Monte Carlo simulation analysis to determine the required sample size for their study (Sinha et al., 2021). Moreover, previous research has shown that it is not feasible to conduct these analyses when sample size is < 70 (Wurpts & Geiser, 2014). To prepare the data for analysis, it is important to examine missing data. To handle missing data, different methods can be used when conducting LPA/LCA, such as listwise deletion, pairwise deletion, multiple imputation, and full information maximum likelihood (FIML; Sinha et al., 2021). Among these methods, FIML is considered as the best method because it uses all available data to compute the parameter estimates (Sinha et al., 2021).

Some assumptions should also be met with regard to selection of the variables and handling the data. Researchers should consider the assumption of local independence, which implies that indicators within each latent class are required to be independent of each other, and that the latent class variable accounts for all associations among indicators (Collins & Lanza, 2010). Moreover, selecting indicators for inclusion in the analyses should be justified based on theory (Sinha et al., 2021). Another point that should be considered is whether indicators need to be analyzed at the item level or aggregate level, though most researchers recommend aggregate variables (Bauer, 2022). In the case of FLA, this means whether researchers should add FLA as one single variable or add its items in the analyses.

2.2.2. Steps for conducting LPA/LCA

Here, we clarify what needs to be done after LPA/LCA have been selected for data analysis. Based on previous studies (Bauer, 2022; Hickendorff et al., 2018; Weller et al., 2020), we suggest the following steps for conducting LPA/LCA: (1) determining the number of latent classes, (2) interpreting the model, and (3) including correlates in LPA/LCA.

First, researchers need to determine the number of latent classes. This step is considered the most important and the most challenging when conducting LPA/LCA (Bauer, 2022; Hickendorff et al., 2018; Sinha et al., 2021). The procedure begins by comparing different class solutions, starting with a one-class solution and progressively adding more classes, until the best-fitting model emerges (Hickendorff et al., 2018). When comparing models, the best model is chosen based on theory, previous research, goodness-of-fit indices, classification diagnostics, and interpretability of the results (Bauer, 2022; Marsh et al., 2009). One of the main criteria for choosing the best model is the use of goodness-of-fit indices. The most common fit indices include the Bayesian information criterion (BIC), sample-size adjusted Bayesian information criterion (SABIC), and the Akaike information criterion (AIC). Lower values for these indices indicate a better fit. In addition, likelihood ratio tests such as the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo et al., 2001) and the bootstrapped likelihood ratio test (BLRT; McLachlan & Peel, 2000) can be used to test if adding a latent class significantly improves model fit.

Previous research has shown that BLRT can provide a more accurate representation of the number of latent classes than the LMR test (see Nylund et al., 2007, for a more detailed explanation of these criteria). In the case of a non-significant LRT, the model with fewer latent classes is selected. Finally, researchers can use classification diagnostics to evaluate how accurately the model assigns individuals to latent classes (Weller et al., 2020). Two major diagnostic statistics are average latent class posterior probability and entropy, for which values close to 1 (or at least above .80) indicate better model specification (see Weller et al., 2020, for a review).

After selecting the optimal number of latent classes, researchers need to interpret the classes. Researchers usually label the classes based on the class-conditional parameters, theoretical background, and previous empirical studies (Hickendorff et al., 2018). In LCA, class-conditional parameters include class-specific probabilities, which show the likelihood of observing a specific categorical response within each class. In LPA, class-conditional parameters include class-specific means and variances for the continuous variables within each class (Bauer, 2022). Another issue that should be considered is the size of the class (Bauer, 2022). Although some guidelines have been proposed for the minimum class size, such as 50 persons or 5% of the sample (Weller et al., 2020), decisions regarding keeping or discarding a class should also rely on theoretical justifications and interpretability of the class (Bauer, 2022; Weller et al., 2020).

The final step in conducting LPA/LCA is examining the relationships between the latent groups and covariates (Nylund-Gibson & Choi, 2018). It should be noted that this step is not obligatory, but it can provide more insight into classification accuracy (Marsh et al., 2009) and the construct validity of the emerging latent classes (Bauer, 2022). This can include predictors (e.g., sociodemographic variables) or distal outcomes (e.g., willingness to communicate and L2 achievement) of the latent classes. There are two major approaches for analyzing the correlates: the one-step approach and the three-step approach (Bauer, 2022). In the one-step approach, the covariate(s) are simultaneously included in the LPA or LCA model with other variables. For example, gender and proficiency levels could be entered alongside FLA to see how more or less anxious language learners are classified into different classes with regard to their gender and proficiency levels. However, this approach is problematic because it might introduce error to the model and produce biased and misspecified models (Bauer, 2022; Nylund-Gibson & Choi, 2018). In the three-step approach, known as R3STEP, such as the Bolck-Croon-Hagenaars (BCH) method (Asparouhov & Muthén, 2014; Bolck et al., 2004), after determining the number of profiles or classes, each person is assigned to a profile or class based on weighted probabilities accounting for classification errors. Then, these weighted probabilities are used to investigate the relationships between latent profiles/classes and distal outcomes or covariates (Asparouhov & Muthén, 2014; Bolck et al., 2004).

2.3. LPA and LCA in foreign language anxiety and emotion research

Both LPA and LCA have been recently used by second language acquisition (SLA) researchers to study motivational and emotional factors (e.g., Dunn & Iwaniec, 2022; Feng et al., 2023; Lou et al., 2022). Regarding foreign language (FL) emotions, there are a few papers which have used LPA and LCA. In these studies, emotions are either used as observed variables in LPA/LCA (Lou et al., 2022; Wang & Xu, 2024; Zhu et al., 2024) or as covariates of LPA/LCA (Feng et al., 2023; Li et al., 2022; Wang et al., 2021). In what follows, we provide a review of the studies which have included FLA as an observed variable in LPA/LCA.

Zhu et al. (2024) examined latent profiles based on anxiety and enjoyment in reading and writing among 679 Chinese high school students. To select the appropriate number of profiles, they used different criteria, such as log-likelihood, AIC, BIC, SABIC, LMR test, BLRT, and entropy. They found four profiles: “moderate-enjoyment/moderate-anxiety” (24.3% of the sample), “moderate-enjoyment/low-anxiety” (48.6% of the sample), “high-enjoyment/moderate-anxiety’’ (8.8% of the sample), and “low-enjoyment/high-anxiety” (18.3% of the sample). Then they examined two aspects of imaginative capacity as predictors of the profiles using multinomial logistic regression and the R3STEP command. They further examined how the four profiles predicted story continuation writing performance using the BCH method and found that the “moderate-enjoyment/low-anxiety group” scored significantly higher than the “low-enjoyment/high-anxiety group.” A major contribution of this study lies in its nuanced examination of the relationship between FL enjoyment and FL anxiety in the context of language learning using LPA. While previous research has consistently shown that FL enjoyment positively correlates with language learning outcomes and FL anxiety negatively correlates with them, this study revealed a more complex interplay between these variables. Specifically, it demonstrated that individuals could be categorized into separate profiles based on their levels of FL enjoyment and anxiety. These profiles provided valuable insights that could inform targeted pedagogical interventions tailored to the needs of specific student groups.

Wang and Xu (2024) used LPA to examine how different positive (pride, hope, and enjoyment) and negative writing emotions (anger, anxiety, shame, boredom, and hopelessness) formed distinct profiles. They used AIC, BIC, SABIC, LMR test, BLRT, and entropy to select the appropriate number of profiles. They also considered the group size to be at least 5% of the whole sample. Accordingly, they found three profiles: “moderate-type,” characterized by average levels of negative and positive emotions, represented 45.2% of the participants; “negative-type,” characterized by high levels of negative emotions and low levels of positive emotions, represented 43% of the participants; and “positive-type,” characterized by high levels of positive emotions and low levels of negative emotions, represented 11.8% of the participants. Following this, Wang and Xu (2024) performed ANOVA to examine how these three groups differed in terms of writing buoyancy, motivation, and proficiency. They found that the "positive-type" group had higher buoyancy and motivation than the other two groups, and the "moderate-type" group had higher buoyancy and motivation than the "negative-type" group. Moreover, they found that the "positive-type" group scored higher on writing proficiency, but no difference was found between "moderate-type" and "negative-type" groups. Similar to Zhu et al. (2024), this study showed that the links between emotions are complex and that person-centered approaches can better capture this complexity than variable-centered approaches. Another unique contribution of this study was the dominance of "moderate-type" and "negative-type" groups, implying that most of the participants in this study experienced moderate levels of positive and negative emotions, followed by participants who experienced high levels of negative emotions and low levels of positive emotions. Based on the ANOVA results, which highlighted the more adaptive role of the "positive-type" group, it can be inferred that teachers should take steps to reduce negative emotions while simultaneously fostering positive emotions among students in "moderate-type" and "negative-type" groups.

Lou et al. (2022) investigated the profiles of the mindest system by including language mindsets, achievement goals, language anxiety, persistence, and positive reappraisals as observed variables in LPA. They used AIC, BIC, SABIC, LMR test, and entropy to select the appropriate number of profiles. They found three profiles: "fixed" profile representing 21.8% of the sample, "growth" profile representing 20.5% of the sample, and "mixed" profile representing 57.7% of the sample. According to Lou et al. (2022), participants included in the fixed profile exhibited lower levels of mastery goals, persistence, and positive reappraisal, but higher levels of language anxiety and performance-avoidance goals compared to those in the growth profile. The dominant group was the "mixed mindset" profile, in which participants endorsed both fixed and growth mindsets and had various goals for language learning, including strong performance-approach, performance-avoidance, and fairly strong mastery goals. They were also generally persistent but experienced anxiety when using the L2. Lou et al. (2022) also used the BCH method to examine how the three profiles predicted distal outcomes including course grades and engagement. They found that participants in the growth profile were more engaged than participants in the mixed and fixed profiles, and that participants in the mixed profile were more engaged than participants in the fixed profile. Similar results were obtained for course grades; however, only the difference between the growth profile and the fixed profile was significant. Then, they used multinomial logistic regression to examine how gender, years of learning experience, ESL status (whether English was a second language for them), level of the language course (1 to 4), and perceived competence predicted profile membership. They found that only perceived competence predicted profile membership as participants who reported higher perceived competence were more likely to belong to the growth profile than to the fixed and mixed profiles. Similarly, participants with higher perceived competence were more likely to belong to the mixed profile than to the fixed profile. Using LPA, this study showed that the majority of the participants had a mixed mindset profile, something which cannot be obtained using variable-centered approaches. This finding is a novel contribution that challenges the traditional dichotomous view of mindsets, in which learners are categorized into either fixed or growth mindset groups. Regarding the role of FLA in the mindset system, it was found that different language mindset profiles experienced different levels of FLA.

2.4. Predictors and outcomes of FLA

In this study, we examined two predictors and two outcomes of FLA profiles, informed by previous theoretical and empirical research. First, we focused on two important outcomes of FLA: WTC and achievement goals. WTC refers to language learners' readiness to communicate with others using the L2 (MacIntyre et al., 1998). Previous research has indicated that FLA is a high-evidence correlate of WTC (see the meta-analysis by Elahi Shirvan et al., 2019). L2 learners who experience anxiety are less willing to communicate in a second language. In addition, achievement goals refer to the underlying reasons and intentions individuals have for pursuing achievement-related tasks (Elliot & Thrash, 2001). A well-known conceptualization of achievement goals considers three types of goals: mastery goals (i.e., competence development and mastering a task), performance-approach goals (i.e., outperforming others), and performance-avoidance goals (i.e., avoidance of showing incompetence). Previous research has shown that mastery-goals are negatively related to FLA (e.g., Barabadi & Khajavy, 2020; Feng et al., 2023; Lou et al., 2022), that performance-approach goals are negatively (Barabadi & Khajavy, 2020) or not significantly linked to FLA (Feng et al., 2023; Lou et al., 2022), and that performance-avoidance goals are usually positively related to FLA (Feng et al., 2023; Lou et al., 2022). In addition, we examined the role of age and gender as two predictors of FLA as previous research has found that age and gender can affect FLA (see Papi & Khajavy, 2023, for a review).

3. Current study

In this section, we demonstrate an application of LPA to FLA. We conducted LPA on FLA items to see how participants in the study could be grouped under distinct profiles based on their reports of anxiety. Then, we examined how different FLA profiles could predict three achievement goals (i.e., mastery goals, performance-approach goals, and performance-avoidance goals) and willingness to communicate (WTC). Moreover, we examined the predictors of the FLA profiles based on participants' age and gender. Therefore, the following research questions were addressed in this study:

RQ1: What distinct profiles of foreign language anxiety (FLA) can be identified among FL learners based on their responses to the FLA scale?
RQ2: How can different FLA profiles predict willingness to communicate and achievement goals?
RQ3: How can different FLA profiles be predicted by FL learners' age and gender?

4. Methods

4.1. Participants

A total of 384 tertiary-level EFL learners (56.3% female) from a university in the north-east of Iran participated in this study. Our sample size was large enough to conduct LPA/LCA, consistent with the guidelines discussed earlier (Howard & Hoffman, 2018). Participants' age ranged from 18 to 20 (*M* = 18.66, *SD* = .72). The participants were undergraduate students studying humanities, social sciences, and engineering. They were all taking a compulsory general English course at the university. Participation was entirely voluntary, and data collection took place during regular classroom sessions.

4.2. Instrumentation

To gather the data, we used a paper-and-pencil questionnaire (see Appendix A for the list of items) which was in participants' native language (i.e., Persian). Participants responded to all items with response options ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

4.2.1. Foreign language anxiety

To measure FLA, we used six items from Horwitz et al. (1986) which were translated by Khodadady and Khajavy (2013) into Persian. A sample item is "I become nervous when I don't understand all the words that English teacher says."

4.2.2. Achievement goals

To measure achievement goals, we used 16 items from Khajavy, Bardach, et al. (2018). The original scale was developed and validated in Persian, and we adopted it for use in the present study. We measured three aspects of achievement goals, including mastery goals (six items, e.g., "because I want to know more"), performance-approach goals (five items, e.g., "so I will have better grades than other students"), and performance-avoidance goals (five items, e.g., "so I won't be worse than other students"). All items were introduced with the prompt "I want to study English. . . ."

4.2.3. Willingness to communicate

To measure WTC, we used seven adapted items from Peng and Woodrow (2010) which were translated by Khajavy et al. (2018) into Persian. The items assessed students' willingness to use English in the classroom context. A sample item is: "I am willing to ask my classmates and teacher in English the meaning of an English word."

4.3. Analysis plan

First, we calculated descriptive statistics, normality, and correlations among variables using variable-centered approaches. Then, we conducted LPA. Maximum likelihood estimation with robust standard errors (MLR) was employed to estimate each profile model, beginning with a 2-profile model and extending to a 6-profile model. The optimal profile was chosen by evaluating several fit indices, including AIC, BIC, and SABIC, with lower values indicating a superior fit (Nylund et al., 2007). Additionally, the Lo-Mendell-Rubin likelihood ratio test (LMR; Lo et al., 2001) was applied to assess model fit, with significant differences suggesting that a profile model fits better than the previous one. An entropy value above 0.80 was also considered as it signals a more accurate classification of profiles. While models with more profiles may often yield better fit indices, we prioritized interpretability and parsimony, selecting the simplest model that provided meaningful insights and aligned with the fit criteria (Nylund et al., 2007).

The next step was to examine the predictors and outcomes of the latent profiles. Based on the selected best-fitting profile solution, we simultaneously incorporated all outcome variables (i.e., achievement goals and WTC) as distal outcomes using the manual 3-step BCH method (Asparouhov & Muthén, 2014; Bolck et al., 2004). In Step 1, LPA was used to classify individuals into profiles, and then the BCH procedure created a new dataset with weights that adjusted for classification error (Step 2). Finally, in Step 3, the weighted data were used to examine relationships between profile membership and outcome variables (see Appendix B for code). This procedure also allowed for the inclusion of predictors, such as gender, to test whether profiles predicted outcomes while controlling for these variables. To investigate predictors of profile membership, predictor variables were analyzed simultaneously using the R3STEP command (Asparouhov & Muthén, 2014).

5. Results

First, we examined descriptive statistics, normality, and reliability of the scales. As shown in Table 1, all metrics appear to be reasonable, and the scales demonstrate good reliability. The correlation results (see Table 2) highlight the variable-centered approach. Anxiety was negatively associated with willingness to communicate and mastery goals, as well as weakly negatively correlating with performance-approach and gender. Women tended to report higher levels of language anxiety and scored higher on all outcome variables. Given these gender differences, it is important to control for gender in the outcome analysis.

Table 1 Descriptive statistics of anxiety items and observed variables

Variable	*M*	*SD*	Min	Max	*α*	Skewness	Kurtosis
Language anxiety (mean)	2.61	1.08	1.00	5.00	.834	0.23	-0.94
Language anxiety items							
1. I don't feel confident when speaking English in the class.	2.60	1.38	1.00	5.00		0.36	-1.15
2. I get nervous when I don't understand what teacher says in English.	2.69	1.51	1.00	5.00		0.28	-1.42
3. In the English class, I feel shy to answer the questions voluntarily.	2.49	1.48	1.00	5.00		0.44	-1.30
4. I can feel my heart pounding when I'm going to be called on in English class.	2.86	1.56	1.00	5.00		0.09	-1.54
5. I get nervous and confused when I am speaking in my English class.	2.30	1.34	1.00	5.00		0.66	-0.83
6. I become nervous when I don't understand all the words that English teacher says.	2.72	1.46	1.00	5.00		0.25	-1.34
Outcomes							
Willingness to communicate	3.74	0.80	1.00	5.00	.799	-0.70	0.45
Mastery	3.91	0.89	1.00	5.00	.837	-0.93	0.54
Performance-approach	4.21	0.85	1.00	5.00	.820	-1.24	1.27
Performance-avoidance	4.20	0.93	1.00	5.00	.875	-1.36	1.37
Demographic predictors							
Gender	0.56	0.50	0.00(M)	1.00(F)	NA	-0.25	-1.95
Age	18.66	0.72	18.00	20.00	NA	0.60	-0.87

Table 2 Correlations among observed variables

Variable	1	2	3	4	5	6	7
1. Language anxiety	--						
2. Willingness to communicate	-.413**	--					
3. Mastery goal	-.404**	.629**	--				
4. Performance-approach goal	-.127*	.333**	.480**	--			
5. Performance-avoidance goal	-.036	.209**	.351**	.723**	--		
6. Gender	.172**	.171**	.228**	.201**	.166**	--	
7. Age	.056	.098	-.009	-.036	-.093	.121*	--

Note. *$p < .05$. **$p < .01$

5.1. Identifying the number of FLA profiles

Goodness-of-fit indices for the tested models can be seen in Table 3. We selected the 5-profile solution as the final model because it provided a better fit compared to the 4-profile solution, as indicated by the LMR (see Table 3). The 5-profile model also had the highest entropy, reflecting clearer classification, and a reasonable distribution of participants across all profiles. Moreover, based on the changes in AIC, BIC, and SABIC, we observed that there were big differences between the 5- and 4-profile solutions (ΔAIC, ΔBIC, and ΔSABIC = 60.77, 33.12, and 55.33, respectively), suggesting the 5-profile solution was better than the 4-profile solution.

Table 3 Fit indices for FLA profiles: 1-profile to 6-profile solutions

# of profiles	LL	AIC	BIC	aBIC	Entropy	Class sizes	Smallest class %	LMR (*p*)
1	-4096.354	8216.707	8264.115	8226.041	NA	NA	NA	NA
2	-3755.122	7548.244	7623.306	7563.022	0.847	205, 179	46.6%	<.001
3	-3685.630	7423.261	7525.978	7443.483	0.878	176, 67, 141	17.4%	.0004
4	-3625.149	7316.298	7446.670	7341.965	0.890	169, 72, 59, 84	15.4%	.0022
5	-3587.764	7255.527	7413.553	7286.639	0.891	112,57,106,76,33	8.6%	.0094
6	-3562.223	7218.447	7404.127	7255.003	0.872	121, 52, 26, 67, 48, 70	6.7%	.0153

Note. LL = log-likelihood. AIC = Akaike Information Criterion. BIC = Bayesian Information Criterion. aBIC = adjusted BIC. LMR-LRT = Lo-Mendell-Rubin adjusted likelihood ratio test. The best model is bolded

Although the 6-profile solution initially appeared to offer a marginally better fit, it had several drawbacks. The smallest class in the 6-profile model included only 26 participants, raising concerns about stability and interpretability. Additionally, the entropy decreased compared to the 5-profile solution, and the additional profile was not meaningfully distinct from the existing ones, offering limited theoretical or practical value. Moreover, based on the changes in AIC, BIC, and SABIC, we observed that there was little change between the 5- and 6-profile solutions (ΔAIC, ΔBIC, and ΔSABIC = 37.08, 9.43, and 31.64, respectively), suggesting the 6-profile solution was not much better than the 5-profile solution.

Therefore, we determined that the 5-profile solution struck the best balance between model fit, class size, and interpretability.

Table 4 Means, standard errors, and significant differences among all indicator variables

Profile name	Low anxiety	Medium anxiety	High anxiety (all)	High physiological response	High anxiety around teacher
n	112	57	106	33	76
% of participants	29.2%	14.8%	27.6%	8.6%	19.8%
Item	*M*(*SD*)	*M*(*SD*)	*M*(*SD*)	*M*(*SD*)	*M*(*SD*)
1. I don't feel confident when speaking English in the class.	1.669 (1.303)[d]	2.410 (1.303)[bc]	3.655 (1.303)[a]	2.358 (1.303)[c]	3.163 (1.303)[ab]
2. I get nervous when I don't understand what teacher says in English.	1.144 (0.305)[d]	2.426 (0.305)[b]	4.422 (0.305)[a]	1.824 (0.305)[c]	4.467 (0.305)[a]
3. In the English class, I feel shy to answer the questions voluntarily.	1.325 (1.228)[d]	2.218 (1.228)[bc]	3.859 (1.228)[a]	2.725 (1.228)[b]	1.863 (1.228)[c]
4. I can feel my heart pounding when I'm going to be called on in English class.	1.405 (0.471)[c]	1.759 (0.471)[b]	4.408 (0.471)[a]	4.217 (0.471)[a]	1.671 (0.471)[bc]
5. I get nervous and confused when I am speaking in my English class.	1.267 (1.198)[d]	2.017 (1.198)[c]	3.247 (1.198)[a]	2.567 (1.198)[b]	2.507 (1.198)[bc]
6. I become nervous when I don't understand all the words that English teacher says.	1.515 (1.429)[c]	2.763 (1.429)[b]	3.683 (1.429)[a]	2.835 (1.429)[b]	3.294 (1.429)[ab]

Note. The *z* scores are based on latent factor scores. [abc] Different superscripts in the same row represent significantly different values ($p < .05$). The highest rated profile(s) for each item is bolded

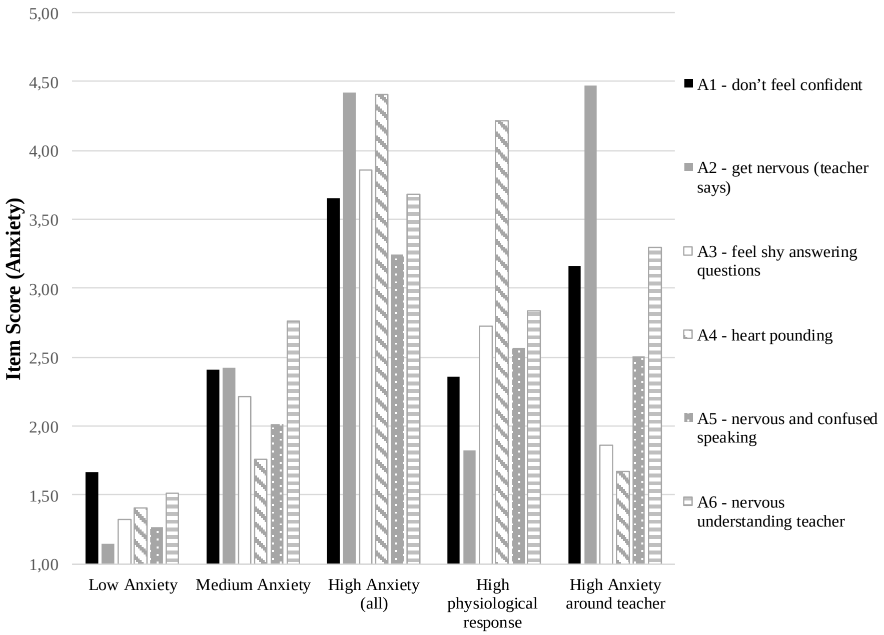

Figure 1 Five-profile solution for FLA: Item score comparison (A higher, positive score indicated a stronger rating of the corresponding item)

As shown in Figure 1 and Table 4, we labeled the five profiles as (1) *low anxiety*, (2) *medium anxiety*, (3) *high anxiety* (all), (4) *high physiological response*, (5) *high anxiety around teacher*. The *low-anxiety* profile and *high-anxiety* profile represent the largest profiles, with 29.2% and 27.6% of the sample, respectively. The Wald tests showed that the differences between these two profiles were distinctive (all significantly different, $p < .05$), representing the opposite ends of language anxiety. In between the *high-anxiety* and *low-anxiety* profiles, there is a *medium-anxiety* profile, representing 14.8% of the sample. This group is also significantly different from the *high-* and *low-anxiety* profiles in all items (all significantly different, $p < .05$).

The profile analysis also revealed two "hidden groups." These two groups reported the highest anxiety only on certain items: *the high-physiological-response* (8.6%) and *the high-anxiety-around-teacher profile* (19.8%). The *high-physiological-response* profile showed medium responses in all items, except for the one item about physiological response ("I can feel my heart pounding when I'm going to be called on in English class"), which was rated as high as the high anxiety group. The *high-anxiety-around-teacher* profile, on the other hand, scored medium levels across most items, except for an item related to teachers ("I get nervous when I don't understand what teacher says in English"). This item was the highest among the five profiles and is not statistically different from the *high-anxiety* profile. Notably, the second-highest rated item in this group was also teacher-related (i.e., "I become nervous when I don't understand all the words that English teacher says"), which was rated comparable to that of the *high-anxiety* group, although the difference from the *medium-anxiety* and *high-physiological-response* groups was not statistically significant. Altogether, these two "hidden groups" (i.e., *high-physiological-response* and *high-anxiety-around-teacher* profiles) represent 28.4% of the sample, but in a variable-centered approach, these two groups would be considered around the medium level in terms of anxiety.

5.2. Differences in outcomes of FLA profiles

Figure 2 and Table 5 present the means of outcome variables for each profile. Willingness to communicate varied significantly across profiles. As expected, students in the *low-anxiety* group had the highest WTC, whereas those in the *high-anxiety* profile showed the lowest WTC. Although the other three profiles (*medium anxiety, high physiological response,* and *high anxiety around teachers*) were significantly different from the *high-* and *low-anxiety* profiles, these three profiles were similar in WTC. In other words, students who displayed high anxiety mostly around the teacher or through physiological responses were more willing to communicate than those in the actual high-anxiety group.

Table 5 Means (and SE) of outcomes for each profile

Outcome variable	Low anxiety	Medium anxiety	High anxiety (all)	High physiological response	High anxiety around teacher
1. Willingness to communicate	3.995	3.410	3.054	3.605	3.333
	(0.077)[a]	(0.121)[b]	(0.097)[c]	(0.099)[b]	(0.121)[b]
2. Mastery goal	4.095	3.550	3.212	3.599	3.392
	(0.093)[a]	(0.141)[b]	(0.108)[c]	(0.139)[b]	(0.118)[bc]
3. Performance-approach goal	4.171	3.977	3.853	3.958	3.864
	(0.092)[a]	(0.141)[ab]	(0.106)[b]	(0.150)[ab]	(0.139)[b]
4. Performance-avoidance goal	4.130	3.847	4.074	3.871	3.998
	(0.107)[a]	(0.154)[a]	(0.110)[a]	(0.175)[a]	(0.137)[a]

Note. Values with different superscripts in the same row represent significantly different values ($p < .05$). Controlled variable: gender

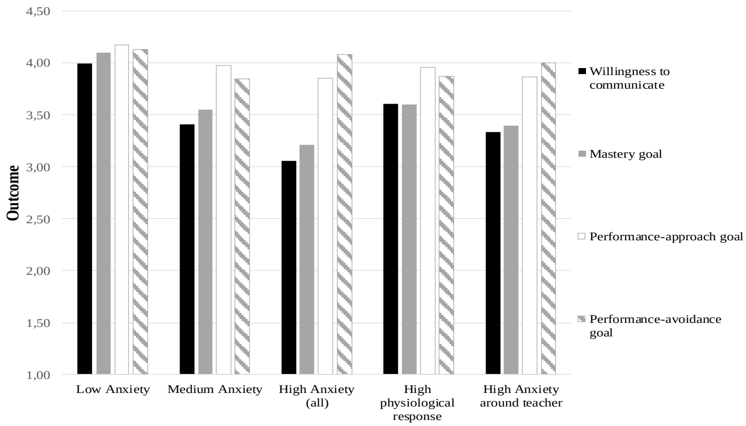

Figure 2 Descriptive statistics for outcome variables across FLA profiles

We also found that students in different profiles were different in their mastery goals. Among *low-*, *medium*, and *high-anxiety* profiles, students in the *low-anxiety* profile showed the highest mastery goals, whereas the *high-anxiety* profile showed the lowest mastery goals, and the medium-anxiety profile was in between (all significantly different from each other, $p_s < .05$). However, the *high-physiological-response* profile was similar to the medium-*anxiety* and *high-anxiety-around-teacher* profiles, whereas the *high-anxiety-around-teacher* profile was not different from the *medium-anxiety, high-anxiety*, or *high-physiological-response* profiles.

Similarly, regarding the performance-approach goals, we found that the *low-anxiety* profile reported higher performance-approach goals than the *high-anxiety* and *high-anxiety-around-teacher* profiles. However, those in the *high-anxiety, medium-anxiety, high-anxiety-around-teacher*, and *high-physiological-response* profiles were similar. Finally, we did not observe any profile differences in performance-avoidance goals.

5.3. Differences in predictors of FLA profiles

The results of the multinomial logistic regression analyses predicting profile membership are shown in Table 6. We found that only gender predicted group membership. Specifically, women (vs. men) were more likely to be in Profile 3 (*high anxiety*) and Profile 4 (*high physiological response*) compared to Profile 1 (*low anxiety*). Women (vs. men) were less likely to be in Profile 5 (*high anxiety around teacher*) compared to Profiles 3 and 4.

Table 6 Joint group membership prediction with multinomial logistic regression

Profile comparison	1 vs. 2		1 vs. 3		1 vs. 4		1 vs. 5		2 vs. 3		2 vs. 4		2 vs. 5		3 vs. 4		3vs. 5		4 vs. 5	
	β	OR	β	OR	β	OR	β	OR	β	OR	β	OR	β	OR	β	OR	β	OR	β	OR
Gender	0.483	1.621	1.227**	3.412	1.186**	3.274	-0.058	0.944	0.745	2.106	0.703	2.020	-0.541	0.582	-0.041	0.960	-1.285**	0.277	-1.244**	0.288
Age	-0.340	0.712	0.013	1.013	0.094	1.098	0.259	1.295	0.352	1.422	0.433	1.543	0.598	1.819	0.081	1.085	0.246	1.279	0.165	1.179

Note. $^{*}p < .05$. $^{**}p < .01$. OR = odds ratio.

6. Discussion

Using LPA, we found five distinct latent FLA profiles, including *low anxiety, medium anxiety, high anxiety, high physiological response*, and *high anxiety around teacher*, capturing the complexity of FLA. They provide a nuanced understanding of FLA and go beyond a simple high versus low comparison in variable-centered approaches. First, students in the *low-anxiety* profile consistently reported low scores across all items. This suggests that this group was relatively comfortable in the English class. Second, students in the *medium-anxiety* profile reported moderate levels of anxiety, which were more maladaptive to their WTC and mastery goals compared to those in the *low-anxiety* profile. Third, the *high-anxiety* group reported the highest scores for all the anxiety items (except for the item about high anxiety around teacher). This profile included learners with the highest level of anxiety and lowest self-confidence, which might be related to a stressful classroom context or past negative experiences (see Papi & Khajavy, 2023). This profile represents the most anxious group, whose learning might have been more impaired by anxiety compared to that of other groups (see Botes et al., 2020; Teimouri et al., 2019; Zhang, 2019). This can be supported by the lowest levels of willingness to communicate and mastery goals reported by these students.

In addition to these expected profiles based on the intensity of anxiety (i.e., low-, medium-, and high-anxiety profiles), we found two other profiles with unique characteristics of FLA based on students' emotional manifestations and triggers: high physiological response and high anxiety around teacher. It seems that there were students in this group who had medium levels of anxiety, but they experienced anxiety primarily through somatic symptoms such as an elevated heart rate.

This distinguishes them from all other groups and makes them a unique group of language learners with a special type of anxiety experience. Somatic anxiety refers to physiological symptoms of anxiety such as sweating, trembling, and increased heart rate (Ree et al., 2008). Finally, in the case of the *high-anxiety-around-teacher* group, to which one-fifth of the participants belonged, we found that these participants had medium levels of anxiety, but their anxiety went up especially when they struggled to comprehend their language teacher in the L2. This finding points to the role of teacher-student dynamics in shaping anxiety levels in language classrooms. This is consistent with previous research showing that not understanding language teachers might be stressful (Khajavy & Vaziri, 2024).

These FLA profiles also varied significantly in their WTC. Students in the *low-anxiety* group reported the highest WTC, while those in the *high-anxiety* group exhibited the lowest. Interestingly, students in the *medium-anxiety*, *high-physiological-response*, and *high-anxiety-around-teacher* profiles showed similar levels of WTC, but these were significantly higher than those of the high-anxiety group. Based on correlations (a variable-centered analysis), we observed that there was a negative relationship between FLA and WTC ($r = -.41$; medium effect size), consistent with previous correlational research (Khajavy et al., 2018; Li et al., 2025). This means higher levels of FLA were associated with less WTC (Elahi Shirvan et al., 2019). However, our LPA findings suggest that although higher FLA was generally associated with reduced WTC, not all profiles with relatively high anxiety affected WTC to the same extent. That is, the relationship between FLA and WTC is more complex than a simple negative correlation. This highlights the importance of distinguishing between different types of anxious L2 learners when examining the impact of anxiety on their WTC. Specifically, medium-level anxiety and anxiety related to teacher interactions or physiological responses may not inhibit communication as severely as high anxiety does. These findings deepen our understanding of the link between FLA and WTC, emphasizing that not all anxiety profiles equally hinder communication.

Regarding achievement goals, we also obtained results that are more complex than and complement the simple correlations derived from variable-centered approaches (Barabadi & Khajavy, 2020; Feng et al., 2023; Lou et al., 2022). We found that students in the *low-anxiety* profile reported the highest mastery goals, while those in the *high-anxiety* profile showed the lowest mastery goals, though this was not statistically significant compared to the *high-anxiety-around-teacher* profile. However, students in the *medium-anxiety*, *high-physiological-response*, and *high-anxiety-around-teacher* groups reported almost similar levels of mastery goals. Similarly, for performance-approach goals, we found that students in the *low-anxiety* group reported more performance-approach goals than those in the *high-anxiety* and the *high-anxiety-around-teacher* groups.

No significant difference was found among students in the *medium-anxiety, high-anxiety, high-physiological-response*, and *high-anxiety-around-teacher* profiles. Finally, no profile differences were found in performance-avoidance goals. The overall pattern of findings indicated that students in the *low-anxiety* profile endorsed a mixture of all achievement goals, including mastery, performance-approach, and performance-avoidance goals. This suggests that lower levels of anxiety can be linked to better learning and performance goals, consistent with previous studies (Feng et al., 2023). On the other hand, students in other anxiety profiles were dominated by performance-approach and performance-avoidance goals, while mastery goals were less prominent. This suggests that higher levels of anxiety may constrain students' ability to focus on learning for skill development, changing their priorities toward either demonstrating competence or avoiding failure (Feng et al., 2023).

Finally, although the variable-centered approach showed that women in general reported higher levels of language anxiety compared to men, we found more nuanced gender differences. Women (vs. men) were more likely to belong to the *high-anxiety* group and *high-physiological-response* groups than to the *low-anxiety* group. Moreover, the likelihood of women (vs. men) belonging to the *high-anxiety-around-teacher* profile was lower than the likelihood of being in the *high-anxiety* and *high-physiological-response* groups. While based on the results obtained from the variable-centered approaches, women reported higher levels of FLA, LPA provided additional information about the relationship between gender and FLA. For example, women may be less likely to be categorized as highly anxious around the teacher, even though they are more likely to be in the group that shows more physiological responses associated with anxiety.

7. Pedagogical implications

Our study identified five distinct groups of language learners with different levels of self-reported FLA. These findings can support teachers in recognizing the diverse emotional profiles of their students, acknowledging that learners vary not just in the intensity of their anxiety but also in how it manifests and what situations provoke it. This awareness can guide teachers in designing more targeted interventions that address the unique needs of each anxiety profile. For example, students with high anxiety related to teacher interactions may benefit more from teacher support that fosters a sense of autonomy and mastery (e.g., emphasizing that mistakes are treated as part of the learning process instead of as judgment from the teacher). On the other hand, learners showing strong physiological responses might respond better to stress-reduction strategies, including mindfulness techniques, as their anxiety is mostly somatic. Meanwhile, students in the high-anxiety group could more broadly benefit from the strategies mentioned above, but they may require additional emotional support, along with confidence-building activities to help them manage their anxiety. Altogether, a single anxiety-reduction strategy or intervention should not be one-size-fits-all. Instead, it should be thoughtfully adapted to meet the emotional needs of diverse learners in the classroom. It should be noted that many of these practices benefit all students with different levels of anxiety and are beyond just reducing anxiety by, for example, improving self-confidence.

Research indicates several ways educators can help learners manage language anxiety and benefit from more positive classroom experiences. For example, promoting learners' ideal L2 self and growth mindset is linked to less anxiety, whereas emphasizing ought-to L2 self and fixed mindset may heighten it (e.g., Jiang & Papi, 2022; Lou & Noels, 2020). Supporting students in emotional regulation can be another helpful approach to regulate anxiety. For example, "reappraising anxiety as excitement" has been found effective in reducing anxiety and improving performance (Brooks, 2014). Moreover, supportive teachers who build rapport and trust can not only lower learners' anxiety, but also shape more positive emotional experiences such as enjoyment (Hejazi & Sadoughi, 2023). These findings suggest that language educators can support their students by fostering positive self-concepts, building supportive relationships, and teaching strategies to reframe anxiety. While these strategies may benefit all students, in light of our current findings, we suggest that future research should explore which practices are most effective for learners with different levels and characteristics of FLA.

8. Limitations

Results of this study should also be interpreted while considering some limitations. First, in this study, we used LPA to examine cross-sectional data. More research is required to examine how FLA profiles longitudinally develop and are linked to WTC and achievement goals. Second, the fourth profile (high physiological response) was found based on only one item, which was about heart rate. There are other physiological responses to anxiety which were not included in the scale. Third, LPA/LCA usually takes an exploratory approach to data analysis, while theoretical considerations might be less applied (Hickendorff et al., 2018). To deal with this limitation, researchers can use LPA/LCA to test theories (Hickendorff et al., 2018). Finally, running LPA/LCA often requires a rather large sample size of 500, although 200 is adequate (Howard & Hoffman, 2018). This means LPA/LCA cannot be used with small sample sizes. These limitations imply that LPA/LCA can be used as complements to variable-centered approaches, rather than as replacements for them.

9. Conclusion

In this study, we provided an overview and guidelines for conducting LPA/LCA, along with an application of LPA in FLA research. Our study showed that person-centered approaches complement the variable-centered approaches in examining language anxiety, providing additional insights that variable-centered approaches often overlook. For example, we identified two distinct FLA profiles (i.e., *high physiological response* and *high anxiety around teacher*) that go beyond the usual dichotomy of low- and high-anxiety students typically revealed through variable-centered approaches. Based on the current findings and our literature review of LPA/LCA, we recommend that SLA researchers who study L2 emotions incorporate person-centered approaches, not as a replacement for more traditional variable-centered approaches, but as a tool to gain a more comprehensive understanding of learners' experiences.

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APPENDIX A

Questionnaire items

Communication anxiety (adapted from Horwitz et al., 1986, Khodadady & Khajavy, 2013)

1- I don’t feel confident when speaking English in the class.
2- I get nervous when I don’t understand what teacher says in English.
3- In the English class, I feel shy to answer the questions voluntarily.
4- I can feel my heart pounding when I’m going to be called on in English class.
5- I get nervous and confused when I am speaking in my English class.
6- I become nervous when I don’t understand all the words that English teacher says.

Willingness to communicate (adapted from Peng & Woodrow, 2010)

1- I am willing to do a role-play in English with my classmate sitting next to me. (e.g., talking about favorite food).
2- I am willing to role-play different situations in English in front of my classmates (e.g., ordering food from restaurant).
3- I am willing to translate a spoken utterance from Persian into English in my class.
4- I am willing to ask the teacher in English to repeat what he/she just said in English because I didn’t understand.
5- I am willing to ask my classmates and teacher in English how to pronounce a word in English.
6- I am willing to ask my classmates and teacher in English the meaning of an English word.
7- I am willing to give a short speech in English to the class about my favorite food with notes.

Achievement goal (adapted from Khajavy et al., 2018)

I want to study English…

Mastery

1- because I want to know more.
2- because I like the challenge.
3- because difficult exercises stimulate me.
4- so I can expand my knowledge.
5- to discover something new.
6- because I would like to know how to solve the exercises.

Performance approach goals

1- so I will be successful at university.
2- so I will get good grades.
3- so I will have better grades than other students.
4- so other people will think that I am good.
5- so other people will consider me to be a good student.

Performance avoidance goals

1- so I won’t get low grades.
2- so I won’t do poorly at university.
3- so I won’t get lower grades than other students.
4- so I won’t look bad in front of other people.
5- so I won’t be worse than other students.

Appendix B

Analysis code (Mplus)

1. Latent profile analysis (an example of 5 profile solutions)

```
VARIABLE:
CLASSES = C(5);
USEVARIABLES = Gender Age A1-A6 wtc mastery app avo;
MISSING ARE ALL (-999);

ANALYSIS: TYPE = MIXTURE;
ESTIMATOR = MLR;

MODEL:
%OVERALL%

MODEL:
%OVERALL%

%c#1%
[A1-A6];

%c#2%
[A1-A6];

%c#3%
[A1-A6];

%c#4%
[A1-A6];

%c#5%
[A1-A6];

OUTPUT:
RESIDUAL SAMPSTAT CINTERVAL MOD TECH1 TECH7;
```

Outcome model (with control variable) – 3 step – BCH approach

Step 1 – See Latent Profile Analysis (above)
Step 2 –BCH weights -- save bcweights (using WTC as an example)

```
VARIABLE:
CLASSES = C(5);
USEVARIABLES = Gender Age A1-A6 wtc mastery app avo;
Auxiliary = wtc Gender;
MISSING ARE ALL (-999);
ANALYSIS: TYPE = MIXTURE;
STARTS = 2000 500;
MODEL:
Savedata:
File IS WTC.dat; SAVE = bchweights;
```

Step 3 – compare group differences on wtc with control variables

```
VARIABLE:
USEVARIABLES = wtc Gender W1-W5;
! W1-W3 are new variables based on Step 2
```

```
CLASSES = C(5);
Training = W1-W5(bch);
MISSING = *;
DATA: FILE IS WTC.dat; ! Grade.dat is saved from Step 2
ANALYSIS: TYPE = MIXTURE;
ESTIMATOR = MLR; STARTS = 0;
MODEL:
%OVERALL%
wtc ON Gender;
%C#1%
[wtc](a);
%C#2%
[wtc](b);
%C#3%
[wtc](c);
%C#4%
[wtc](d);
%C#5%
[wtc](e);
MODEL CONSTRAINT:
new(ab, ac, ad, ae, bc, bd, be, cd, ce,de );
ab = a - b;
ac = a - c;
ad = a - d;
ae = a - e;
bc = b - c;
bd = b - d;
be = b - e;
cd = c - d;
ce = c - e;
de = d - e;
```

3. Predictor model (R3STEP command)

```
VARIABLE:
CLASSES = C(5);
USEVARIABLES = A1-A6;
Auxiliary = Gender (R3STEP)
Age(R3STEP);
MISSING ARE ALL (-999);
ANALYSIS:
TYPE = MIXTURE;
ESTIMATOR = MLR;
MODEL:
%OVERALL%
%c#1%
[A1-A6];
%c#2%
[A1-A6];
%c#3%
[A1-A6];
```

```
%C#4%
[A1-A6];

%C#5%
[A1-A6];

OUTPUT:
CINTERVAL RESIDUAL MOD SAMPSTAT TECH1 TECH7;
```