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Original Paper

Identifying L2 Regulatory-mode Profiles for Chinese Undergraduate Students

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Abstract

Motivation shapes and influences students' cognition, emotion, and behavior in learning a foreign language. Two important motivation constructs regarding regulatory modes (assessment and locomotion) have been introduced to second/foreign language learning. These two L2 regulatory modes, measured by Regulatory mode scales (RMS, Teimouri et al., 2022), were used to map profiles among students learning English as a foreign language (EFL) from Iran. However, it is not clear whether their L2 regulatory-mode profiles are able to generalize to samples in a different culture (e.g., China) and at a different developmental age. To attain these aims, this study collected data from a sample of Chinese undergraduate students. Results showed that a Chinese version of the English questionnaire was appropriate for ensuring the validity and reliability of the measure when administering this questionnaire to this population.

Keywords

L2 motivation, L2 regulatory mode, L2 assessment, L2 locomotion, latent profile analysis

1. Introduction

Motivation is a key predictor of how students set goals and pursue goals in language learning (Teimouri et al., 2022). Successful language learners want to be effective in their language learning with regard to experiencing control over and understanding their learning (Papi & Hiver, 2020). Assessment and locomotion concern how students are motivated (i.e., monitor and control their choice of goals and strategies in achieving their language learning goals (Teimouri et al., 2022). Four L2 regulatory-modes profiles (Teimouri et al., 2022) were first identified and among Iranian English learners. Their samples for these four profiles were conducted with cluster analyses (e.g., K-mean method) for 459 English-major undergraduates aged from 18 to 50 years old in sample 2). Considering that the two regulatory modes may interact to influence how Chinese students learn English, the interplay between the two motivation constructs cannot be fully grasped if they are considered in isolation using variable-centered approaches. Therefore, it is critical that the interrelations between L2 assessment and L2 locomotion are mapped to enable the identification of distinct patterns/configurations of the two constructs among Chinese undergraduate students. To bridge this gap, this study used a different person-centered approach to investigate the L2 regulatory-mode profiles in a sample of Chinese non-English major undergraduate students.

2. Research Aims

The present research endeavors to identify whether a set of L2 regulatory-mode profiles could exist for Chinese undergraduate students. In doing so, the first goal of the present investigation is to estimate models that could best capture the interrelations between L2 assessment and L2 locomotion for this population. Investigating a set of L2 regulatory-mode profiles is important because (i) Teimouri et al.(2022) found adaptive profiles and less adaptive profiles in English learners; and (ii) teachers and students may use the profile information and alter part of the profile to motivate their goal pursuit during learning a foreign language (Teimouri, Papi, & Tahmouresi, 2022).

3. Regulatory mode theory

Kruglanski et al (2000) proposed that motivation should go beyond focusing on attaining desired outcomes when pursuing goals (Kruglanski, Thompson, Higgins, Atash, Pierro, Shah, & Spiegel, 2000). People have two regulatory modes that concern the ways/manners/strategies how they self-regulate their goal pursuit (Kruglanski, Thompson, Higgins, Atash, Pierro, Shah, & Spiegel, 2000). Assessment mode pertains “the comparative aspect of self-regulation concerned with critically evaluating entities or states, such as goals or means, in relation to alternatives in order to judge relative quality” (Kruglanski et al., 2000, p. 794). Students high on assessment tend to prioritize comparing and choosing the right goals/means. Consequently, strong assessment is a strong positive predictor of L2 anxiety, intended effort, and attention, but a weak predictor of L2 willingness to communicate, and also a weak negative predictor of language proficiency (Teimouri, Papi, & Tahmouresi, 2022). That is, in the English class, when students have strong L2 assessment, although they may have high levels of intended effort to speak English, they tend to have high levels of anxiety about speaking English, are not willing to communicate in English and may not have a high level of proficiency of speaking the language.

The second regulatory mode, locomotion, concerns “the aspect of self-regulation concerned with movement from state to state and with committing the psychological resources that will initiate and maintain goal-related movement in a straightforward and direct manner, without undue distraction or delays” (Kruglanski et al., 2000, p. 794). In the English class, strong locomotion students tend to have high levels of joy and intended effort as well as attention, very strong willingness to communicate in English, and low levels of anxiety; they tend to high levels of language proficiency (Teimouri, Papi, & Tahmouresi, 2022).

Two independent L2 self-regulatory modes were established and measured by two reliable and valid Regulatory Mode Scales (Teimouri et al., 2022) with data collected from two EFL student samples in Iran (N = 459 each; including one sample of university students). These authors investigated the relations between assessment/locomotion and a set of EFL/L2 motivation factors (attention, anxiety, joy, intended effort, and willingness to communicate) (Papi & Hiver, 2020).

4. Method, Samples, Instruments, and Data Analysis

Respondents were 274 non-English major undergraduate students attending a university in central northern China. Convenience sampling was used in the present study. There were no missing data because the survey was administered on an online platform (Wenjuanxing) and no questions were allowed to skipped. The sample consisted of 74 males (27.0%) and 200 females (73.0%). For the sample, 257 first-year students accounted or 93.8% and 17 second-year students accounted for 6.2%.

The questionnaire comprised two sections, using a bilingual version (Chinese–English). The first section included demographic information with open questions, including gender, which year they were in, and their major. The second section included items that measured L2 regulatory-mode motivation. L2 Regulatory Mode Scales (RMS; Teimouri et al., 2022) were used to measure assessment and locomotion regarding speaking English in English class. Four items were used to gauge assessment (e.g., I often analyze the structure of my sentences before speaking English). Five items were used to capture locomotion (e.g., I'd like to speak in my English class rather than watch others speaking). Each item was assessed on a 7-point Likert scale ranging from 1 (strongly disagree) to 4 (neutral) to 7 (strongly agree).

Prior to conducting latent profile analyses, confirmatory factor analyses were conducted to examine the factor validity of the scores of each scale. Latent profile analyses were employed to uncover/identify a set of patterns/configurations/combinations defined by L2 assessment and L2 locomotion. The two L2 regulatory-mode variables were called profile indicators for the latent profile model specification. The different patterns of relative/absolute mean scores were called latent profiles; the students assigned/classified into each profile were called latent classes (Soo Hoo & Hodis, 2026).

When estimating latent profile analysis models, each participant is assigned to one latent profile/class based on the most average posterior probabilities that a student belongs to a particular subgroup/class/profile (Soo Hoo & Hodis, 2026). This mix-modelling approach is more appropriate for student membership, instead of forcing students into a group based on high/low mean scores of profile indicators which is a common method used in cluster analyses (e.g., the approach used in Teimouri et al., 2022). To ensure model stability and parsimony, a common approach was taken (local independence of profile indicators). That is, within each profile identified, profile indicators are not correlated and keep independent from each other (Soo Hoo & Hodis, 2026). This practice is consistent with the latent profile analyses recommended (Soo Hoo & Hodis, 2026) and with the theory that the two L2 regulatory mode constructs are independent from each other (Teimouri, Papi, & Tahmouresi, 2022)

When deciding on the optimal/best number of latent profiles that the data supported, a set of statistical criteria were used (Soo Hoo & Hodis, 2026). First, three commonly used information criteria were used (including AIC, BIC, SABIC). For the three information criteria, a model that has the lowest value best fit the data. In addition, two likelihood ratio tests were used (ALRT and BLRT); when the p-values associated with these test criteria were below .05, the model under consideration was regarded as providing a better fit to the data than its counterpart model with one fewer class (Soo Hoo & Hodis, 2026). Another commonly used index is entropy that measures accuracy in profile separation. When entropy values were larger than .70, the model of interest would be acceptable (Soo Hoo & Hodis, 2026). After estimating latent profile models and deciding on the best number of profiles that fit the data, these profiles were to be described.

5. Results

Before conducting latent profile analyses, a series of confirmatory factor analyses were performed with Mplus, version 8.3 (Muthen & Muthen, 2019). Results showed that no problems of multivariate normality violation were found (see results reported by Wang, 2025 as part of a large project). We stopped at estimating the 6-class model because a model with the smallest profile size less than 15 participants would be not stable and be problematic to compare with other profiles (Soo Hoo & Hodis, 2026). Therefore, models with 6 or more classes were not considered in the present research. Table 1 summarized the statistical indexes employed to inform choosing the best number of classes for the sample. Results presented in Table 1 show that the model having 2-class (see Table 2) was abandoned because p-ALRT was far larger than .05 and not significant and its entropy was far below .70. Although The 3-class model had an acceptable entropy value, it was also not considered due to its non-significant p-ALRT value. In addition, the profiles uncovered in the 3-class model (see Table 3) were parallel because they differed only in levels (i.e., high-high, average-average, low-low patterns of the two regulatory mode mean configurations). These results associated with the 3-class model just reflected the variable-centered results (e.g., positive correlations between the two constructs uncovered by the confirmatory factor analyses).

Subsequent analyses were restricted to models with four and five classes. The 5-class (see Table 5) seemed to be supported by most of the statistical criteria. It was associated with the lowest information criteria (AIC, BIC, SABIC), significant likelihood test values (both values for ALRT and BLRT were less than .05), and the highest entropy value. However, it had a class that had fewer participants than 15 (14 very close the cutoff value). When the information criteria were all low, the sudden drop of BIC between models would be considered; the large difference of BIC between models stopped at the 4-class model. Therefore, the 5-class model was not retained for consideration.

For the remaining model, the 4-class model had all the support from the statistical criteria. Specifically, it had reasonable level of entropy (above .70), BIC's sudden drop, significant likelihood tests (ALRT and BLRT), and the class had the reasonable profile size (15 cases). Taken together, the 4-class model was supported by all the statistical criteria for model fit whereas the 2-class model was supported by the least number of the model fit criteria, and the remaining models were only supported by some criteria. Therefore, all these aspects suggest that the 4-class model was the best fit for the data. Below, the characteristics of the each class/profile in the chosen 4-class model (see Table 4) were briefly described.

Class 1 (8.03% of the total sample), the second less common profile, was distinguished by very low levels of both assessment and locomotion; thus the Class1 was labeled as low assessment and low locomotion. In this profile, assessment was slightly higher than locomotion. This profile reflected that students in this subgroup would be low in truth effectiveness and low in taking control of their goal pursuit in speaking English. This profile also suggested that students would have limited confidence in their academic abilities and a weak sense of personal control over outcomes regarding speaking English (Teimouri, Papi, & Tahmouresi, 2022).

Class 2 (46.72%), the most common profile, was characterized with assessment and locomotion levels slightly above the sample average; thus the Class 2 was labeled as above average assessment and above average locomotion. In this profile, assessment was also slightly higher than locomotion. This profile reflected that students in this subgroup would be above average regarding both truth effectiveness and taking control of their goal pursuit in speaking English. This profile also suggested that students would have some confidence in their academic abilities and kind of sense of personal control over outcomes regarding speaking English. They might be ambivalent about their understanding their English speaking experience and taking actions in speaking English (Teimouri, Papi, & Tahmouresi, 2022).

Class 3 (39.78% of the total sample), the second common group, captured a mixed-profile. This profile was defined by slightly below average assessment but low locomotion; thus the Class 3 was labeled as average assessment and low locomotion. Within this profile, assessment was much higher than locomotion. The students classified in this profile might believe in their abilities, they were low in taking action regarding English speaking (Teimouri, Papi, & Tahmouresi, 2022).

Finally, Class 4 (5.47% of the total sample) represented a high-functioning group, distinguished by high assessment and very high locomotion; thus the Class 4 was labeled as high assessment and very high locomotion. Within this profile, assessment was comparable to locomotion. This profile reflected very strong confidence, high self-regulation, and a robust belief in personal agency in speaking English (Teimouri, Papi, & Tahmouresi, 2022). Together, these four profiles illustrated meaningful differences in students' assessment and locomotion regarding English speaking in their class.

Comparing the four profiles uncovered with those four profiles reported by Teimouri et al. (2022) showed similarities and differences. In the two studies discussed, high assessment and locomotion profiles were uncovered. However, in Teimouri et al. (2022) assessment was higher than locomotion; however, the two construct were comparable in this study. These types of profiles provided support for high levels of assessment and locomotion working together (Teimouri, Papi, & Tahmouresi, 2022).

A second type of profiles was also found in both studies: the low assessment and low locomotion profiles. However, close examination of this type of profiles showed that assessment was lower than locomotion in Teimouri et al. (2022); in contrast, the pattern was different in this study.

Because the profiles in Teimouri et al. (2022) were based on high/low levels of L2 regulatory mode using cluster analyses, there were no profiles defined by average levels of L2 regulatory mode. In their study, the two other profiles were characterized by either low/high on one construct. Importantly, profile studies are important because they are appropriate uncovering varying levels of profile indicators in real-life contexts (Higgins, 2012). Latent profile analyses are important to uncover profiles with different levels of constructs, instead of the high/low levels that are used in variable-centered approach. Although profiles are useful for advancing understanding of how L2 regulatory-mode constructs interplay within individuals, problems in uncovering profiles are often encountered (e.g., low variability in profile indicators and overlapping profiles). Some researchers warn that there would be no profiles in complex data (Harring & Hodis, 2016).

Table 1. The Model Fit Results of Statistical Criteria Latent Profile Analyses

Model	*SPS*	*LL*	*Params*	*AIC*	*BIC*	*SABIC*	*p-ALRT*	*p-BLRT*	*Entropy*
2-Class	88	-884.515	7	1783.030	1808.322	1786.126	0.1159	0.0000	0.568
3-Class	19	-845.584	10	1711.169	1747.300	1715.592	0.0934	0.0000	0.793
4-Class	15	-830.090	13	1686.180	1733.151	1691.931	0.0009	0.0000	0.786
5-Class	14	-820.140	16	1672.280	1730.090	1679.358	0.0395	0.0000	0.811

Note. SPS = the smallest class/profile size associated with any of the classes identified by the given model; LL = log-likelihood; AIC = Akaike Information Criterion; BIC=Bayesian Information Criterion; SABIC = sample-size adjusted BIC; *p*-ALRT = the p-value associated with the Lo-Mendell-Rubin adjusted likelihood ratio test; *p*-BLRT = the *p*-value associated with the bootstrapped likelihood ratio test; Values in bold indicate that the corresponding index suggests extracting a model solution with the specific number of classes/profiles.

Table 2. Descriptive Statistics for Classes and Total Samples of the Two-Class Model

Latent Class	%	Assessment Mean	Assessment Variance	Locomotion Mean	Locomotion Variance
Class 1	34.08	3.163	0.926	2.148	1.188
Class 2	65.92	4.891	0.926	3.678	1.188
Total	100	4.302	1.597	3.156	1.714

Table 3. Descriptive Statistics for Classes and Total Samples of the Three-Class Model

Latent Class	%	Assessment Mean	Assessment Variance	Locomotion Mean	Locomotion Variance
Class 1	20.44	2.719	0.744	1.828	0.752
Class 2	72.63	4.583	0.744	3.265	0.752
Class 3	6.93	6.169	0.744	5.935	0.752
Total	100	4.302	1.597	3.156	1.714

Table 4. Descriptive Statistics for Classes and Total Samples of the Four-Class Model

Latent Class	%	Assessment Mean	Assessment Variance	Locomotion Mean	Locomotion Variance
Class 1	8.03	1.866	0.753	1.338	0.396
Class 2	46.72	4.778	0.753	3.811	0.396
Class 3	39.78	3.989	0.753	2.335	0.396
Class 4	5.47	6.229	0.753	6.349	0.396
Total	100	4.302	1.597	3.156	1.714

Table 5. Descriptive Statistics for Classes and Total Samples of the Five-Class Model

Latent Class	%	Assessment Mean	Assessment Variance	Locomotion Mean	Locomotion Variance
Class 1	7.66	1.743	0.540	1.288	0.377
Class 2	47.81	4.774	0.540	3.801	0.377
Class 3	33.58	3.656	0.540	2.353	0.377
Class 4	5.11	5.589	0.540	2.007	0.377
Class 5	5.84	6.231	0.540	6.312	0.377
Total	100	4.302	1.597	3.156	1.714

6. Future Directions of Research and Conclusion

Higgins theory of motivation (2012) proposed that four constructs capture three ways of effectiveness strivings in goal pursuit (i.e., assessment,locomotion as well as promotion and prevention (Higgins, 2012). Further research could investigate whether these four work together in motivating English learners in university/high school. Future research could also collect data from samples that include English major students and non-English major students (undergraduate and postgraduate students) to examine similarities/differences of the profiles uncovered regarding their relations with other L2 motivation factors (such as those examined in Teimouri et al., 2022).

Moreover, future research could investigate the L2 regulatory-mode profiles for students in the Western cultures/countries. The L2 literature regarding the type of profiles was limited to university students in Eastern countries (e.g., China, Iran). Such profile studies could be conducted in samples of L2 learners other than English in Western countries/cultures to examine whether generalizable profiles might be uncovered. In addition, future research could also examine the regulatory mode profiles in domain-general or in L2 for international students who learn Chinese in China. Recent studies have been informed by Soo Hoo and Hodis (2026) to identify profiles defined by satisfaction/frustration of three basic psychological needs among US and New Zealand undergraduate students and the associations between these profiles and a set of important motivation factors related to promotion and prevention (Soo Hoo & Hodis, 2026). More research is needed to investigate L2 regulatory-mode profiles and need satisfaction/frustration profiles and examine their relations with a broader set of motivation factors and achievement outcomes for students in language learning.

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