Research Article

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Understanding salient trajectories and emerging profiles in the development of Chinese learners’ motivation: a growth mixture modeling approach

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Abstract: Based on the theoretical framework of the L2 Motivational Self System (L2MSS), the present study aims to make a methodological contribution to L2 motivation research. With the application of a novel growth mixture modeling (GMM) technique, the study depicted developmental trajectories of three motivational variables (ideal L2 self, ought-to L2 self, and L2 learning experience) of 176 Chinese tertiary-level students over a period of two semesters. Results showed two to three salient classes with typical developmental patterns for the three motivational variables respectively, with which the study gained fresh insights into the developmental processes of motivation beyond the individual level. Our study further established three main multivariate profiles of motivation characterized by a distinct combination of different motivational variables. The findings extend our understanding of motivational dynamics, providing a nuanced picture of emergent motivational trajectories systemically. Additionally, GMM has shown to be an effective and applicable method for the identification of salient patterns in motivation development, which leads to practical implications.

Keywords: emerging profiles; growth mixture modeling; learning motivation; salient trajectories

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1 Introduction

The introduction of complex dynamic system theory (CDST) to the research on second language (L2) motivation has brought paradigm shifts in conventional L2 motivation studies and fueled the application of innovative research methods. Guided by CDST, a number of studies have examined the changing and dynamic process of motivation development over time and identified new patterns that emerged in the developmental process (e.g., Chan et al. 2015; Waninge 2015). While these studies have shed light on the complexity and dynamics in L2 motivation, they explored the emerging and changing motivational processes mainly at the individual level with a limited number of learners (Henry 2015; Piniel and Csizér 2015; Waninge 2015). Recently, researchers (e.g., see Hiver et al. 2021 for a review) have begun to recognize the significance, as well as the possibility, of using innovative methodologies in L2 motivation research to depict individual-level trajectories of motivational development, to identify salient trajectories of learning motivation at a relatively global level, and to draw inferences about the mechanisms of motivational development holistically (Hiver and Papi 2019).

Growth mixture modeling (GMM) technique (Muthén 2004) has gradually been recognized as a novel approach to achieving this research goal. Specifically, it allows to identify latent classes of learners within a population, with each class showing a distinct developmental trend with regard to their L2 performance and learning behavior over time. This classification of learners allows the prediction of membership within a given subpopulation. As such, the present study adopts a GMM approach to identifying salient motivation trajectories (i.e., showing distinct developmental trends) and the emergent multivariate profiles of motivation (i.e., configurations of different motivational components) of 176 tertiary-level Chinese EFL (English as foreign language) learners over two semesters.

The GMM approach offers promise for advancing L2 motivation research in terms of theory and pedagogy. Theoretically, it enables the assessment of the interindividual difference in intraindividual changes in a larger population. By classifying learners who show qualitatively different processes of motivation development into different groups, the GMM technique enriches our understanding of L2 learners’ motivational dynamics beyond the individual level. Practically, the exploration of the differences between learners with distinct patterns of change allows language educators to strategically scaffold language learners’ learning motivation and hence to actively intervene their language learning processes. What’s more, as Chinese learners constitute the largest English learner group in the world (You and Dörynei 2016; Yu and Lowie 2020), investigating the developmental processes of Chinese EFL learners at the relatively global level can
contribute to our understanding of language learning motivation of EFL learners in broader contexts, potentially pushing L2 motivation research and CDST-based language development research forward.

2 Literature review

2.1 Distinct trajectories of motivational development

By combining the possible selves theory (Markus and Nurius 1986) and self-discrepancy theory (Higgins 1987), Dörnyei (2009) proposed L2 Motivational Self System (L2MSS), which contains three subcomponents: Ideal L2 Self, Ought-to L2 Self, and L2 Learning Experience. The Ideal L2 Self refers to the perfect future self that L2 learners desire to be identified with. The Ought-to L2 Self relates to the outside attributes that the L2 learners believe ought to follow and to avoid negative results in the future (e.g., expectations, obligations). And L2 learning experience concerns “situated, executive motives related to the immediate learning environment/experience” (e.g., teachers, peers) (You and Dörnyei 2016, p. 498). A holistic, dynamic view is recently appearing in L2 motivation research, recognizing that “motivation has adaptive and self-organizing properties, with feedback loops that continuously integrate internal and external contexts and act as reinforcing or counteracting forces, creating nonlinear changes in levels of motivated behavior” (MacIntyre et al. 2015, p. 423). In line with this view, researchers, guided by the CDST theoretical framework, have increasingly conducted L2 motivation studies that pay explicit attention to the time dimension and to explore the processes of motivational change and development at various timescales. While some investigated how language learners’ motivation evolves over time (Papi and Hiver 2020; Piniel and Csizer 2015; Zheng et al. 2021), others identified possible attractor states (e.g., Al-Hoorie 2018; Chan et al. 2015; Dörnyei and Ryan 2015). Attractor states, from a CDST perspective, indicate the state that a system stabilizes towards over time or the outcome that the system falls into through adaptive changes (Hiver and Al-Hoorie 2020).

Qualitative methods were widely adopted to investigate motivational dynamics. For example, in Motivational Dynamics in Language Learning, the first volume devoted to exploring motivational dynamics, Chan et al. (2015) traced learners’ motivational dynamics with a RQM technique. In a retrodictive manner, they first focused on the end states of the focal system and then explored how the system evolved to reach the outcomes observed. The study generated seven learner archetypes with varying degrees of motivation, emotions, cognition and behavior based on teacher reports. Then, among the seven learner archetypes identified,
they focused on one specific type (i.e., the highly competitive and motivated student, with some negative emotions) and provided a retrospective account of a student’s motivational dynamics. RQM used in the study was able to trace back the developmental trajectories that resulted in the learner archetypes, shedding light on the signature dynamics of the motivation system related to each learner archetype. More recently, Papi and Hiver (2020), by adopting a retrospective longitudinal design, investigated the emergent motivational trajectories based on language learning histories of six Iranian males at different stages of language learning experiences. The results showed adaptive interactions between value, truth, and control related motivations, and revealed different motivational trajectories that emerged in the context. In addition, they emphasized that each motive would gain more strength through its interaction with other motives as well as with the context in which it was situated, rather than it worked individually. By assessing learners’ retrospective narratives, these studies have gained insight into the dynamics, as well as stability, characteristic of L2 motivation at the individual level. However, despite these fine-grained observations of L2 motivation, learners’ retrospective narratives are imperfect representations of the reality, because they are often imaginative recomposition of past events and expectation of future ones (Panattoni and McLean 2018).

So far, only a limited number of studies have adopted quantitative approaches to investigating motivation profiles. For example, Papi and Teimouri (2014) used a quantitative cluster analysis method to identify different learner types of L2 motivation. Their results showed that there were five types of learners with different motivation profiles, each profile characterized by a distinct combination of motivational, emotional, and linguistic components. Their study emphasized the significance of considering typical motivation profiles, which may contribute to L2 motivation research both theoretically and pedagogically. It should be noted that the findings reported in Papi and Teimouri (2014) were based on data collected from Iranian students, which may not be readily generalizable to students from other learning contexts. As such, it would be interesting to testify whether similar motivational profiles would emerge in different socio-educational contexts (e.g., Chinese EFL learning context). In addition, the quantitative method (i.e., cluster analysis) adopted in the study requires researchers to make subjective decisions on the optimal number of clusters (Warschauer et al. 2019), which may influence, to some degree, the validity of the research findings yielded.

In a more recent study, Zheng et al. (2020) used Q methodology to trace how Chinese English majors’ motivational patterns adapted and evolved over 1.5 years. Unlike previous research that focused on L2 learning, this study investigated learners’ motivation to learn a third language (L3) Spanish learning in addition to L2 English learning from CDST perspective. In this study, Zheng et al. (2020)
observed two motivation profiles emerging from the data. One has a dominating translingual and transcultural orientation that develops into more constitutive ideal multilingual selves, while the other has a dominating instrumental orientation that generates decreasing motivational forces. However, the English majors targeted in their study, also limited in number, were studying in a prestigious university located in a cosmopolitan city in China. Compared to students from other average universities in other regions and areas of China, these students tend to exhibit a relatively high level of learning motivation for having a more supportive learning environment. Moreover, Chinese non-English major university students constitute the majority of the English learning population in China, so they could, to some extent, represent the English learning in China. It is thus warranted to examine Chinese EFL learners’ L2 motivation development (by targeting non-English majors) so as to provide a more comprehensive picture of L2 motivational dynamics and to provide helpful pedagogical suggestions for enhancing EFL learning in a broader sense. The present study was thus designed to bridge this research gap, by adopting an innovative GMM technique.

3 Methodological advances: GMM

Although different quantitative techniques (e.g., cluster analysis, Q methodology) have been applied to L2 motivation research in different learning contexts, quantitative investigations are rather scarce in literature. Examining L2 motivation quantitatively can potentially generate new sights into developmental dynamics of motivation across individuals, based on which motivation researchers are able to infer, or even to generalize, to a wider population. In line with this advancement, the present study aims to identify L2 learners’ salient trajectories and typical multivariate profiles of motivation, and recognizes GMM technique, a modeling-based technique with strong validity (Warschauer et al. 2019), as a prominent way of doing so.

GMM, which has been successfully applied to recent motivation research (e.g., Guay et al. 2021; Lee and Ju 2021), can appropriately “develop multifactorial, nonlinear, and probabilistic models that are a better fit for such complex and dynamic language learner data” (Hiver et al. 2021: 5). Specifically, it can distill “inter-individual differences in intra-individual change [while] taking into account unobserved heterogeneity (different groups) within a larger population” (Jung and Wickrama, 2008: 303) based on initial states and shape of the growth trajectories of motivation. For instance, Guay et al. (2021), by adopting GMM, identified five distinct profiles of Canadian secondary school learners’ self-determined motivational dynamics over time. The five motivational trajectories were termed low, high-stable,
increasing, moderate, and high respectively. Instead of investigating the development process of each motivation component individually, their study holistically examined the global level of self-determined motivation with a synergic consideration of different motivation components. In another study, Lee and Ju (2021) investigated the diverging motivation trajectories of South Korean learners in terms of three different extrinsic motivation components and learners’ competence beliefs. By adopting a parallel-process GMM, the study identified three distinct classes for external regulation, four distinct classes for introjected and identified regulation respectively. Results of the study provided a more nuanced picture of the development of multidimensional motivation from the self-determination theory.

However, no attempt has been made to investigate the salient dynamic trajectories of L2 learning motivation under the L2MSS framework. L2MSS has been fruitfully applied to guide quantitative survey research in diverse learning environments, particularly in the Chinese EFL context (Boo et al. 2015; Csizér 2019; You and Dörnyei 2016), and has also been validated as “an integrative synthesis of several previous constructs and approaches in L2 motivation research” (You and Dörnyei 2016, p. 497). In light of this, the present study, based on L2MSS framework, is intended to identify salient trajectories and emerging multivariate profiles of Chinese EFL learners’ motivation over time with a GMM technique.

4 The present study

The main purpose of the present study is to identify Chinese EFL learners’ salient patterns of motivation development holistically and longitudinally. Based on L2MSS, we first track trajectories of motivation depicted with the initial states and the shape of the growth over time and analyze the interindividual differences in intraindividual changes with a relatively large population. Then, we identify meaningful classes of similarly structured individuals (i.e., individuals who share similar patterns of motivational development) through a quantitative GMM approach. Specific research questions are formulated as follows:

RQ1. Can we identify salient trajectories for the development of ideal L2 self, ought-to L2 self and L2 learning experience respectively?

RQ2. Can we identify emerging multivariate profiles of motivation among 176 Chinese learners?

For RQ1, according to the results of prior research (e.g., Guay et al. 2021; Lee and Ju 2021), we expect that two to four salient subgroups that show similar developmental trajectories (i.e., with an increasing or a decreasing trend) would be identified for each component of motivation.
And for RQ2, we predict that two to four main (with larger population) motivational profiles in terms of the combination of different motives of motivation would emerge among 176 Chinese learners, based on previous work by Papi and Teimouri (2014).

4.1 Participants

Our study included 198 non-English major freshmen from different subjects (e.g., physics, chemistry, mechanical engineering, etc.) at a comprehensive university (key university) in northern China. Their average NCEE (National College Entrance Examination) score of English was 129 (Range = 44, SD = 8.62). In this higher education institution, non-English majors only learn English during their first and second years of university study. After entering this university, they would be required to take an English placement test through Speexx and then be assigned to different levels of English courses. Speexx is an online language learning and testing platform that screens language levels of learners based on Common European Framework of Reference for Language (CEFR). The participants in this study were awarded the beginning level of proficiency (CEFR B1.1) and were divided into 5 parallel classes randomly. The first author was the instructor of the 5 parallel classes, and gave their English lesson 90 min per week respectively. Using a convenient sampling method (Dörynei 2007), all the learners in these 5 parallel classes were chosen as participants of the present study with their consent.

4.2 Measures

The motivation questionnaire had 17 items that assess learners’ motivation based on the L2MSS framework (Dörnyei 2009). Items indicative of participants’ motivation were mainly adapted from previous research instruments (e.g., Papi and Teimouri 2014). The measure of items was scored on a 6-point Likert scale ranging from 1 to 6, with 1 indicating strongly disagree or not at all and 6 referring to strongly agree or very much. The questionnaire had been piloted and successfully applied in Peng et al. (2020) (see Appendix A), in which the focused participants were in the same age range at a university of same level as the participants targeted in the present study.

The motivation questionnaire consisted of two parts: Part I collected participants’ background information such as gender, educational level, language proficiency. Part II included items that measured learners’ motivational states. The variables indicative of learner motivation included ideal L2 self, ought-to L2 self, L2 learning experience. A reliability analysis was conducted, the Cronbach Alpha
internal consistency coefficient for all the three multi-item scales of six waves rendered satisfactory levels.

*Ideal L2 self* (5 items; $\alpha_{time1} = 0.889; \alpha_{time2} = 0.911; \alpha_{time3} = 0.936; \alpha_{time4} = 0.942; \alpha_{time5} = 0.948; \alpha_{time6} = 0.935), measures learners’ own aspiration and desire for language learning (i.e., expectations).

*Ought-to L2 self* (6 items; $\alpha_{time1} = 0.902; \alpha_{time2} = 0.927; \alpha_{time3} = 0.933; \alpha_{time4} = 0.947; \alpha_{time5} = 0.956; \alpha_{time6} = 0.942), concerns the attributes that one believes one ought to possess (i.e., responsibilities, or obligations) in order to avoid possible negative outcomes.

*L2 learning experience* (6 items; $\alpha_{time1} = 0.807; \alpha_{time2} = 0.905; \alpha_{time3} = 0.917; \alpha_{time4} = 0.922; \alpha_{time5} = 0.936; \alpha_{time6} = 0.932), measures learners’ attitudes, as well as situation-specific motives, related to the immediate learning environment and experience.

### 4.3 Procedures

To identify the salient development trends and profiles of Chinese EFL learners’ motivational involvement in English learning, we adopted a longitudinal research design in line with the CDST perspective that guided the study. Given that language learning motivation may vary in strength at different timescales (de Bot 2015), depicting the temporal, developmental processes that occur at a higher and macro-level (i.e., month) would provide a unique and comprehensive picture of motivational dynamics (Hollenstein 2013). As such, the present study, unlike previous research (e.g., Waninge 2015) that focused on changes at the micro level (i.e., lesson or week), aimed at creating a macro-map of motivation development. Learners were asked to complete the same questionnaire at a 2-month interval over the course of the first two semesters (from October 2020 to August 2021). At the end of the study, the learners completed six times in total. The present study adopted Huixin, an online questionnaire software that can distribute questionnaires to participants’ phones automatically and regularly, to collect the longitudinal motivation data. The first author set the questionnaires to be sent to learners’ phones at time scheduled purposefully during English classes so that she would remind learners to complete the questionnaires on time. Before the research, the first author asked all the learners to download an application called Psychorus on their phones and had them pilot the questionnaire successfully. The overall number of participants at Time 1 was 198. The total sample at each wave was as follows: Time 1 ($N = 198$), Time 2 ($N = 186$), Time 3 ($N = 183$), Time 4 ($N = 178$), Time 5 ($N = 180$), Time 6 ($N = 176$). Only data from participants who completed all six times were included in the present study; as such, the total number of participants of the present study was 176 (52 females, 124 males).
The first author checked with learners who did not complete the questionnaire for detail reasons, and found that some learners left their phones at dormitories accidentally while others missed the notification of questionnaires on their phones when they were having online courses.

4.4 Data analysis

Following the analytic procedure described in Jung and Wickrama (2008), we adopted a three-step process. First, in order to identify the model of change that best represented the motivation data collected in the present study, we conducted a series of single-group models, including intercept only, linear, quadratic, piecewise quadratic, and latent basis (freely estimated time) models. All models were conducted in Mplus version 8.6. To evaluate the goodness-of-fit of these models, we adopted different fit statistics criteria, including comparative fit index > 0.95 (CFI), Tucker-Lewis coefficient > 0.95 (TLI), root mean square error of approximation < 0.06 with a confidence interval upper limit of < 0.06 (RMSEA with CI 90%), and standardized root mean square residual of < 0.06 (SRMR) (Mueller and Hancock 2019).

Then, latent class growth analysis (LCGA) and GMM were estimated successively to generate the optimal number of classes. In the process of identifying the best number of classes fitting the data, we performed an iterative process, starting from a one-class model and adding classes to the model. Because descriptive accuracy and simplicity should both be valued in model selection (Vandekerckhove et al. 2015) and given the relatively small sample size of present study, we only tested one-through four-class solutions to find the best model fitting the data collected. Following Berlin et al. (2014) and Lee and Ju (2021), we ran several sets of models, in which we freely estimated means and variances for latent variables representing intercept and slope over time, and covariance between intercept and slope.

Moreover, to further investigate the detailed membership of each latent class assignment, Savedata: SAVE = CPROB; FILE IS xxx.txt; was added to GMM syntax, which led to different motivational configurations (i.e., distinct combinations of different motivational components). To determine the best model that fits to the data, several fit indices were compared and interpreted (Nylund et al. 2007), such as Akaike Information Criterion (AIC), Bayesian information criterion (BIC), and sample-size-adjusted BIC (SSBIC). Lower AIC, BIC, SSBIC values indicate a better model fit. It should be noted that BIC and SSBIC were included particularly because BIC is the best and most consistent fit statistic for determining the number of classes (Nylund et al. 2007) and SSBIC is the most accurate criterion fit statistic for small samples (e.g., $N < 500$; Hensen et al. 2007). Besides, we also included other information criteria, such as Entropy, the Adjusted Lo-Mendell-Rubin LRT (ALMRT) and
the bootstrapped likelihood ratio test (BLRT), for a more objective model-fitting and -selecting process (Wang and Bonder 2007). Entropy is an indicator of classification quality which ranges from 0 to 1, higher values indicating more accurate classification of individuals into classes (higher than 0.70 indicate acceptable classification). A significant p-value for ALMRT and BLRT indicate that the model with larger number of classes is favored (Nylund et al. 2007).

5 Findings

In order to identify the model that best represented the six data points, we successively conducted a series of single-group models for each motivation component (i.e., ideal L2 self, ought-to L2 self, L2 learning experience respectively). According to the fit statistics (see Appendix B), the intercept-only, linear, quadratic, and piecewise quadratic models provided a poor fit to the data. Given that CFI and TLI for the latent basic model of growth were larger than the recommended level (>0.95) and that RMSEA and SRMR were also superior to the recommended level (<0.06), latent basis model of growth was considered as the best base model for our later growth mixture analyses and interpretations for L2 motivation. The latent basis model selected is flexible to describe nonlinear development patterns and determine the shape of change best fitting the participants’ data across time (Ram and Grimm 2007).

5.1 Ideal L2 self

The mean in the intercept and slope of the latent basis model differs significantly from zero and is positive (intercept = 3.76, \( p < 0.001 \); slope = 0.04, \( p < 0.001 \)), indicating that mean trajectory developed in a non-linear pattern with increasing growth. Additionally, significant variances were also spotted (intercept = 0.42, \( p < 0.001 \); slope = 0.90, \( p < 0.001 \)). Then, we proceeded to identify latent classes, assessing LCGA models for 1, 2-, 3-, 4-class successively, and the statistical fit indices were shown in Table 1. Four classes had been yielded, the 3-class solution showed lower AIC, BIC, SSBIC and higher entropy value than 2-class, p-value for both ALMRT (\( p = 0.04 < 0.05 \)) and BLRT (\( p < 0.001 \)) were significant. In addition, at 4-class, ALMRT was non-significant (\( p = 0.38 > 0.05 \)), which means a 3-class solution should be rejected in favor of a 4-class solution.

As the condition for within-class heterogeneity was met, we proceeded with running GMM for the final results. The statistical fit indices for the 1-, 2-, 3-class GMM analysis were shown in Table 1. Given the lower AIC, BIC, and SSA-BIC
Table 1: Model fit statistics of LCGA and GMM: Ideal L2 self.

<table>
<thead>
<tr>
<th>No. of classes</th>
<th>Log likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>SSA-BIC</th>
<th>Entropy</th>
<th>ALMRT p-Value</th>
<th>BLRT p-Value</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCGA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Class</td>
<td>−1484.46</td>
<td>2992.92</td>
<td>3030.96</td>
<td>2992.96</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>176</td>
</tr>
<tr>
<td>2 Class</td>
<td>−1362.08</td>
<td>2762.15</td>
<td>2822.39</td>
<td>2762.22</td>
<td>0.87</td>
<td>0.00</td>
<td>&lt;0.001</td>
<td>47;129</td>
</tr>
<tr>
<td>3 Class</td>
<td>−1260.49</td>
<td>2572.97</td>
<td>2655.40</td>
<td>2573.07</td>
<td>0.96</td>
<td>0.04</td>
<td>&lt;0.001</td>
<td>15;129;32</td>
</tr>
<tr>
<td>4 Class</td>
<td>−1200.45</td>
<td>2466.90</td>
<td>2571.52</td>
<td>2467.02</td>
<td>0.93</td>
<td>0.38</td>
<td>&lt;0.001</td>
<td>40;92;12;32</td>
</tr>
<tr>
<td>GMM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Class</td>
<td>−1296.22</td>
<td>2618.45</td>
<td>2659.66</td>
<td>2618.49</td>
<td>−</td>
<td>−</td>
<td>−</td>
<td>176</td>
</tr>
<tr>
<td>2 Class</td>
<td>−1246.48</td>
<td>2526.96</td>
<td>2580.86</td>
<td>2527.02</td>
<td>0.82</td>
<td>0.03</td>
<td>&lt;0.001</td>
<td>121;55</td>
</tr>
<tr>
<td>3 Class</td>
<td>−1200.29</td>
<td>2442.59</td>
<td>2509.17</td>
<td>2442.67</td>
<td>0.85</td>
<td>0.14</td>
<td>&lt;0.001</td>
<td>126;10;40</td>
</tr>
</tbody>
</table>

N = 176. AIC, Akaike information criterion; BIC, Bayesian information criterion; SSABIC, sample-size adjusted Bayesian information criterion; Adjusted LRT, Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BLRT, bootstrapped likelihood ratio test. The values shown in bold indicate the model with the smallest value. N, estimated number of individuals in each class. The numbers in bold refer to the best model fit.
values, higher entropy, and significant likelihood ratio tests, the 2-class solution had the best fit as compared to 1-class and 3-class solutions. Therefore, the 2-class solution was retained, and the class membership of the 2-class solution was reasonably spread (68.2 and 31.8%). The developmental trajectories for two latent classes of ideal L2 self were plotted separately (Figure 1).

Class 1, the slight decrease (68.2%) had a moderate starting point (intercept = 3.90, \( p < 0.001 \)) and negative growth (slope = \(-0.41, p < 0.001\)). Class 2, the moderate increase (31.8%), who initially had weak levels of ideal L2 self (intercept = 3.45, \( p < 0.001 \)), and showed gradual increase over time (slope = 1.14, \( p < 0.001 \)).

### 5.2 Ought-to L2 self

Both the trajectories of mean (intercept = 3.59, \( p < 0.001 \); slope = 0.20, \( p < 0.05 \)) and variance (intercept = 0.57, \( p < 0.001 \); slope = 0.96, \( p < 0.001 \)) showed positively significant increase over time, which was similar to ideal L2 self. The LCGA models yielded four classes, in which the 3-class solution showed lower AIC, BIC, SSBIC and higher entropy value than 2-class, \( p \)-value for both ALMRT (\( p = 0.04 < 0.05 \)) and BLRT (\( p < 0.001 \)) were significant (see Table 2). In addition, the GMM analysis showed that the 2-class solution had the best fit with lower AIC, BIC, SSA-BIC values, higher entropy, and significant ALMRT and BLRT (see Table 2). Thus, the 2-class solution was selected (89.3 and 10.7%).

Class 1, the slight decrease (89.3%) who showed slightly decrease of ought-to L2 self over time. Specifically, Class 1 had a moderate starting point (intercept = 3.81, \( p < 0.001 \)) and negative growth (slope = \(-0.02, p > 0.05 \)). Class 2, the dramatic increase (10.7%), who initially had low levels of ought-to L2 self (intercept = 1.79, \( p < 0.001 \)), and increased sharply at the beginning and turned into a higher level slightly at the later stage (slope = 2.08, \( p < 0.001 \)) (see Figure 2).

### 5.3 L2 learning experience

Unlike the ideal L2 self and ought-to L2 self, the mean trajectory of L2 learning experience differs significantly from zero but is negative (intercept = 3.97, \( p < 0.001 \); slope = \(-0.10, p < 0.05 \)), indicating that the mean trajectory developed in a non-linear pattern with a decreasing trend. In addition, significant variances in the intercept and slope of latent basis model were spotted (intercept = 0.32, \( p < 0.05 \); slope = 0.64, \( p < 0.001 \)). Four classes had been yielded through LCGA models, the 3-class solution showed lower AIC, BIC, SSBIC and higher entropy
Figure 1: Estimated longitudinal trajectories of ideal L2 self (a)–(c): (a) two latent classes, (b) Class 1 – slight decrease, and (c) Class 2 – moderate increase.
Table 2: Model fit statistics of LCGA and GMM: Ought-to L2 self.

<table>
<thead>
<tr>
<th>No. of classes</th>
<th>Log likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>SSA-BIC</th>
<th>Entropy</th>
<th>ALMRT p-Value</th>
<th>BLRT p-Value</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCGA</td>
<td>1 Class</td>
<td>-1404.75</td>
<td>2833.50</td>
<td>2871.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Class</td>
<td>-1416.87</td>
<td>2871.74</td>
<td>2931.98</td>
<td>2871.81</td>
<td>0.86</td>
<td>0.00</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>3 Class</td>
<td>-1352.91</td>
<td>2757.82</td>
<td>2840.26</td>
<td>2757.92</td>
<td>0.90</td>
<td>0.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>4 Class</td>
<td>-1322.81</td>
<td>2711.63</td>
<td>2816.25</td>
<td>2711.75</td>
<td>0.91</td>
<td>0.64</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>GMM</td>
<td>1 Class</td>
<td>-1326.69</td>
<td>2681.37</td>
<td>2725.76</td>
<td>2681.42</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2 Class</td>
<td>-1308.55</td>
<td>2653.10</td>
<td>2710.17</td>
<td>2653.17</td>
<td>0.87</td>
<td>0.04</td>
<td>0.0128</td>
</tr>
<tr>
<td></td>
<td>3 Class</td>
<td>-1317.83</td>
<td>2673.65</td>
<td>2733.89</td>
<td>2673.73</td>
<td>0.79</td>
<td>0.14</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

The bold values represent the best-fitting classes.
Figure 2: Estimated longitudinal trajectories of ought-to L2 self (a)–(c): (a) two latent classes, (b) Class 1 – moderate stable, and (c) Class 2 – dramatic increase.
value than 2-class, $p$-value for both ALMRT ($p = 0.04 < 0.05$) and BLRT ($p < 0.001$) were significant (see Table 3). We proceeded with running GMM for the final results. We had attempted to fit a 4-class model, as the likelihood ratio tests for 3-class model were still significant and variance within and cross classes remains. However, analysis yielded several warning messages when adding a class to the 3-class model. This is mainly due to the sample size and the fact that there were only four students assigned to class 2. Considering the proportion in each of the latent classes is at least 5% (Mara and Carle 2021), we did not improve convergence as the number and type of warnings messages indicated that the 4-class model was not feasible. According to statistical fit indices for GMM analysis (see Table 3), compared to 1-class and 2-class solutions, the 3-class solution had the best fit with lower AIC, BIC, and SSA-BIC values, higher entropy, and significant ALMRT and BLRT. Therefore, the 3-class solution was chosen, and the class membership of the 3-class solution was reasonably spread (5.7, 26.8, and 67.5%).

Class 1, the gradual increase (5.7%) who initially had moderate levels of motivation (intercept = 4.39, $p < 0.001$), and showed gradual increase to a higher level (slope = 1.48, $p < 0.001$). Class 2, the slight decrease (26.8%) who initially had moderate levels of motivation (intercept = 4.14, $p < 0.001$), but decreased slightly with fluctuation over time (slope = −1.02, $p < 0.001$). Class 3, the high stable (67.5%) who had a high-stable level of motivation over time (intercept = 3.88, $p < 0.001$; slope = 0.26, $p < 0.001$) (see Figure 3).

### 5.4 Multivariate profiles of L2 motivation

Based on the detailed information about each participant's latent class assignments in terms of ideal L2 self, ought-to L2 self, and L2 learning experience, the GMM

<table>
<thead>
<tr>
<th>No. of classes</th>
<th>Log likelihood</th>
<th>AIC</th>
<th>BIC</th>
<th>SSA-BIC</th>
<th>Entropy</th>
<th>ALMRT $p$-Value</th>
<th>BLRT $p$-Value</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCGA</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Class</td>
<td>−1395.63</td>
<td>2815.27</td>
<td>2853.31</td>
<td>2815.31</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>176</td>
</tr>
<tr>
<td>2 Class</td>
<td>−1290.01</td>
<td>2618.03</td>
<td>2678.27</td>
<td>2618.10</td>
<td>0.86</td>
<td>0.02</td>
<td>&lt;0.001</td>
<td>141;35</td>
</tr>
<tr>
<td>3 Class</td>
<td>−1195.38</td>
<td>2442.76</td>
<td>2525.20</td>
<td>2442.86</td>
<td>0.90</td>
<td>0.04</td>
<td>&lt;0.001</td>
<td>119;33;24</td>
</tr>
<tr>
<td>4 Class</td>
<td>−1163.90</td>
<td>2393.81</td>
<td>2498.43</td>
<td>2393.93</td>
<td>0.89</td>
<td>0.16</td>
<td>&lt;0.001</td>
<td>8;101;44;23</td>
</tr>
<tr>
<td>GMM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Class</td>
<td>−1211.74</td>
<td>2449.47</td>
<td>2490.69</td>
<td>2449.52</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>176</td>
</tr>
<tr>
<td>2 Class</td>
<td>−1172.08</td>
<td>2378.17</td>
<td>2432.06</td>
<td>2378.23</td>
<td>0.62</td>
<td>0.24</td>
<td>&lt;0.001</td>
<td>116;42</td>
</tr>
<tr>
<td>3 Class</td>
<td>−1146.85</td>
<td>2335.68</td>
<td>2402.26</td>
<td>2335.76</td>
<td>0.81</td>
<td>0.01</td>
<td>&lt;0.001</td>
<td>10;43;123</td>
</tr>
</tbody>
</table>

The bold values represent the best-fitting classes.
Figure 3: Estimated longitudinal trajectories of learning experience (a)–(d):
(a) three latent classes, (b) Class 1 – gradual increase, (c) Class 2 – slight decrease, and (d) Class 3 – high stable.
technique further identified nine motivational profiles, each configured by a distinct combination of the three motivational components (see Table 4). Among them, only three motivational profiles contained larger numbers of learner, they are I1O1E2 (n = 37), I1O1E3 (n = 78), and I2O1E3 (n = 32) respectively, and the rest participants scattered in other patterns with rather small proportion (less than 5%).

6 Discussion

The main purpose of the present study was to identify salient developmental trajectories of motivation and establish multivariate motivational profiles among 176 Chinese learners over the period of two semesters through a novel longitudinal GMM technique. Salient classes were identified for the ideal L2 self, the ought-to L2 self, and the learning experience respectively. And we further established three main motivational configurations, each with a distinct combination of the three motivational components (i.e., ideal L2 self, ought-to L2 self, and learning experience).

6.1 Salient trajectories

With the application of a GMM approach, we identified two salient classes for the learners’ ideal L2 self and ought-to L2 self respectively, and three salient classes for the L2 learning experience. These distinct trajectories corroborate the “levels of reality” (Cilliers and Nicolescu 2012: 716); that is, typical patterns of motivational development would emerge from the data beyond the individual dynamics, as

<table>
<thead>
<tr>
<th>Profiles</th>
<th>Title</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I1 O1 E2</td>
<td>37</td>
</tr>
<tr>
<td>2</td>
<td>I1 O1 E3</td>
<td>78</td>
</tr>
<tr>
<td>3</td>
<td>I1 O2 E2</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>I1 O2 E3</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>I2 O1 E1</td>
<td>7</td>
</tr>
<tr>
<td>6</td>
<td>I2 O1 E2</td>
<td>5</td>
</tr>
<tr>
<td>7</td>
<td>I2 O1 E3</td>
<td>32</td>
</tr>
<tr>
<td>8</td>
<td>I2 O2 E1</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>I2 O2 E3</td>
<td>8</td>
</tr>
</tbody>
</table>

I1 refers to ideal L2 self class 1, I2 refers to ideal L2 self class 2, O1 refers to ought-to L2 self class 1, O2 refers to ought-to L2 self class 2, E1 refers to learning experience class 1, E2 refers to learning experience class 2, E3 refers to learning experience class 3. The three profiles in bold represent the three main motivational configurations.
explicitly pointed out in Baba and Nitta (2021). The existence, as well as the identification, of salient motivational trajectories reported in the present study is consistent with findings in several previous studies (e.g., Guay et al. 2021; Lee and Ju 2021), though under different motivation theoretical framework.

With regard to ideal L2 self, we identified a slight decrease class and a moderate increase class, suggesting that not all the learners have developed their future selves and that the differences indeed existed over time. These two classes have highlighted the particular contribution of the GMM approach to L2 motivation research, for these latent classes might have been ignored if heterogeneity in developmental patterns was not taken into account (Lee and Ju 2021). These distinct trajectories might be related to learners’ exposure to teaching materials or their different English learning histories (You and Chan 2015). Specifically, learners’ ideal L2 self may go upward or downward when they receive positive or negative feedback on progress (Henry 2015; You and Chan 2015). This finding confirms that the ideal L2 self dimension of motivation would change dynamically (i.e., upwardly and downwardly) depending on learners’ assessment of the likelihood of their achievement over time (see also Henry 2015). Additionally, learners in the moderate increase class had reached a significantly higher level of ideal L2 self (from 3.447 to 4.591) over time, meaning that their ideal selves have been substantiating in terms of both desirable social and professional dimensions. From a CDST perspective, the emergence of this occurring trajectory would be regarded as a reflection of attractor states (see, De Bot et al. 2007). That is to say, as a highly internalized motivated learning behavior, learners’ future selves seemed to have become more elaborated and tangible (Lockwood and Kunda 1997) when compared to peers (i.e., students from the same class) who share similar characteristics of ideal L2 self (Henry 2015).

For ought-to L2 self, a slight decrease class and a dramatic increase class were identified, with the majority (89.3%) of the students showing a non-significant decreasing trend. In China, English language education is exam-oriented, and Chinese EFL learners, driven primarily by their ought-to L2 selves (Peterson et al. 2013), may feel obligated (to their parents and teachers alike) to learn English (Taguchi et al. 2009). When they entered university, however, their parents’ influence was comparatively weak (Brown and Wang 2016; Papi and Hiver 2020), for university students have fulfilled their obligations to families by enrolling into high-status universities. Therefore, facing less pressure than they had during NCEE preparation (Yu et al. 2018), learners may show a slight decreasing trend of ought-to L2 selves.

Unlike the ideal L2 self and ought-to L2 self, we have found three latent classes for the learning experience dimension of learning motivation. They are the gradual increase class, the slight decrease class, and the high stable class. The majority
(73.2%) showed a rather high-stable level of English learning experience over two semesters, and even led to a slight increase by the end of this study, indicating that a large population tended to show an increasingly positive attitude toward English learning.

By classifying individuals with shared learning patterns into different groups, the present study can have several pedagogical implications. First, the patterned outcomes regarding the development of L2 motivation enable educators to design and implement individualized interventions tailored for learners with different patterns of motivation, enhancing learners’ learning motivation substantially. Furthermore, since most salient classes of ideal L2 self and ought-to self showed declining patterns (i.e., the slight decrease) over time, some teaching strategies should be adopted to develop learning motivation continuously. For example, imagery training for enhancing learners’ ideal L2 self could be developed, as the “vision of one’s idealized persona is a valid and potent motivator for Chinese learners of English” (You and Dörynjei 2016, p. 513).

Despite the fact that each component of L2MSS showed non-linear developmental trajectories, only the learning experience dimension of motivation developed with a negative trend. This result partly matched the findings in Piniel and Csizer (2015), testifying that though having vivid future images of their ideal L2 self (i.e., have realized the close relevance of English in their future use), some learners still have negative learning experiences.

### 6.2 Emerging motivational profiles

The present study, with the GMM technique, also established three main multivariate motivational profiles, each with a distinct combination of the three motivational components (i.e., ideal L2 self, ought-to L2 self, and learning experience) of the L2MSS. The findings provide further credence for the holistic view that “L2 motives do not always work individually; rather, it is the dynamic interplay between these motives in interaction with the contingencies and affordances of the learning environment that determine learners’ motivational trajectory” (Papi and Hiver 2020: 18).

Profile 1 is I1O1E2, emphasizing that learners in this group had weak scores in almost all motivational components (i.e., the ideal L2 self, ought-to L2 self, and learning experience). English teaching hours in Chinese universities have been reduced sharply for non-English majors compared to junior or senior school, which results in the fact that English is not considered as important as their majors (e.g., physics, chemistry, engineering). That is, instead of having a vivid picture of their future life closely related to English learning, learners merely regard it as a
learning task to be finished (e.g., to pass the final examination) (Papi and Teimouri 2014). Profile 2 is I1O1E3, indicating that learners had weak scores on ideal L2 self and ought-to L2 self, and moderate score on learning experience. Learners in this profile have positive attitudes toward the English learning process, though they have not established a clear vision of their future selves, and are worried about the potential negative consequences associated with teachers’ and parents’ expectations. It might be interesting to point out that both Profile 1 and Profile 2 correspond to Group 1 and Group 2 identified in Csizér and Dörnyei (2005) as well as in Papi and Teimouri (2014). Thus, we may conclude that these two motivation profiles are well-established and reasonably consistent across different learning contexts and learners. Concerning that the focus in these studies were EFL learners, a reconsideration of the role of learners’ language contact in their life-world may be evoked. For example, an adaptive pedagogy that situates language learning as situated and contextualized practice should be considered (Dubreil and Thorne 2017:6) and adopted so as to help learners recognize the significance of English learning related to their ideal L2 selves and/or ought-to L2 selves. Specifically, educators may consider highlighting the importance of English courses at university and encouraging students to develop a vivid picture of their future life in close relation to English usage, potentially leading to the increase in their language learning motivation.

Profile 3 is I2O1E3. Learners in this motivation profile had moderate scores on ideal L2 self and L2 learning experience, but low scores on ought-to L2 self. In other words, they have generally developed the social and professional dimensions of the ideal L2 self, and may have been motivated by their executive motives. That is to say, learners may recognize the significance of passing examinations and developing visions of their future selves that are related to English, but they still tend to show less favorable attitudes towards English learning. This observation of the present study ran counter to the common assumption in motivation research that ideal L2 self is usually conceived as the main source of motivation in language learning (Hiver and Al-Hoorie 2020). It is worth noting that the Profile 3 observed here was the only one inconsistent with prior research by Papi and Teimouri (2014). This discrepancy might be ascribed to the longitudinal design adopted by present study. Existing literature has highlighted the significance of using methods that have an affinity to the time-dependent process of variation to investigate development phenomena (e.g., Lowie 2017). In line with this, we adopted a novel GMM methodology to trace typical trajectories of developmental changes and processes, coupled with multivariate motivational profiles, at the group level, providing insights into the complexity and dynamism of motivation development.
7 Conclusion

Aiming for a methodological contribution to L2 motivation research, the present study adopted a novel GMM approach to identifying salient trajectories and emerging patterns of different motivational variables of Chinese university students over a period of two semesters. The results showed that two salient classes were identified for ideal L2 self and for ought-to L2 self respectively, and three different classes for L2 learning experience. Moreover, three multivariate motivational profiles were established, each with a distinct combination of the three motivational components (i.e., ideal L2 self, ought-to L2 self, and learning experience). The longitudinal findings offer empirical evidence for subtle differences in these theoretically distinct components of L2MSS, emphasizing the multidimensional and dynamic nature of learning motivation. In addition to that, identifying distinct longitudinal trajectories through a sophisticated method (i.e., the GMM technique) is potentially useful for designing and implementing practical interventions and teaching programs tailored for different subgroups of learners. Specifically, for learners who show weaker motivation towards language learning, teachers can be mindful of teaching progress and assign differentiated learning tasks for them. Likewise, for identified individuals who may have stronger motivation towards language learning, teachers can trace the typical learners of this type in depth and explore the reasons that made the learning progress more effective.

As the present study constitutes an initial attempt to investigate L2 motivation through the GMM approach, some limitations should also be noted for further exploration. First, the present study provides a new way that allows us to identify the non-linear developmental patterns of motivation over time and to interpret the distinct features of different learner types which otherwise would be overshadowed in the Chinese EFL context. In future studies, researchers may want to focus on the exploration of potential influencing factors or predictors of salient emerging classes through qualitative methods or mixed methods over a longer period of time. For example, investigating some typical learners of each latent class could reveal the underlying mechanisms behind them. Second, these emerging trajectories and patterns cannot be generalized to learners from diverse contexts due to the ergodicity problem (Lowie and Verspoor 2019). What GMM does allow us to do is to identify the hidden learner groups with different processes of motivation development over time. More research is thus warranted to investigate learners from different learning contexts as motivation dynamics is susceptible to the specific social spatial context (Hiver and Al-Hoorie 2021). Third, it should be noted that some students did not complete the questionnaire all six times, which might have influenced the overall motivational trajectories and configurations.
found and interpreted in the present study, as one of our reviewers kindly pointed out. In spite of these limitations, we hope that the present study, which identified salient trajectories and emerging multivariate profiles of Chinese EFL learners’ motivation over time, has showed the effectiveness and potential of applying this novel GMM methodology in L2 motivation research.

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