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Change over Time in Learners' Mindsets about Learning a Foreign Language

Abstract: Inspired by the recent avenues for longitudinal research in second language acquisition (SLA), in this study we aimed to trace changes in language mindsets over time via a curve of factors model. The data were collected from 437 adult English as a foreign language learners' response to the Language Mindsets Index in four time points. The model fit was accepted and the invariance of the latent factor was attested over time. The findings indicated a negative covariance between the initial level language mindsets and the growth level of the construct. This finding implies that learners with a highly initial level of language mindsets experienced less change in the construct over time and those with a lower level of the construct changed their mindsets more over time. Pedagogical implications of the findings such as language teachers' consideration of growth language mindsets interventions are discussed.

Keywords: *language mindsets, language mindsets index, initial level, growth level, curve of factors model*

INTRODUCTION

Mindsets are described by Dweck (1999) as the beliefs and mental frameworks people have in perceiving and making sense of their social surroundings. Investigating mindsets is of a high value in education as it can predict academic motivation and success (Lou & Noels, 2017). Two general types of mindset were distinguished, entity and incremental, the former marked by a belief in fixed personal abilities and the latter by flexible qualities (Dweck, 1999). As further described by Hong, Chiu, Dweck, Lin and Wan (1999), in challenging conditions, individuals with an entity theory (mindset) soon see failures due to their own lacking efficiency and, thus, feel less self-confident while those with an incremental theory tend to be confident and hard-working to further pursue the goals. The existing body of research into mindsets has increasingly pointed to the domain-specificity of the construct (Dweck, Chiu, & Hong, 1995). The majority of research into mindsets has been in domains other than language learning (Lou & Noels, 2017). The unique features of language learning domain (e.g. the multicultural dimension, and the extended sphere of learning beyond classroom) (Dörnyei &Ushioda, 2009; Gardner, 2010) lead us to expect a unique conceptualization of mindset in this domain (Lou & Noels, 2017). However, the extent to which the factorial structure of language mindsets, as reflected in the scale developed fir its measurement, is stable over time has not been examined yet. In other words, the verification of longitudinal invariance measurement of the language mindsets scale can avoid any misinterpretation regarding analysis of temporal change of the construct. More specifically, given the dynamic turn in the field of SLA with an emphasis on change in Individual difference (ID) variables over time; longitudinal investigation of the construct of language mindsets, via suitable methods for this purpose, can provide deeper insights into the dynamics of this construct.

LANGUAGE MINDSETS

Having different beliefs about the nature of language learning can affect language learners' motivation, acquisition, goal-orientation and learning outcomes (Barcelos & Kalaja, 2011; Horwitz, 1988; Lou & Noels, 2017). It makes a difference whether people see language learning stem-

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ming from an innate, unchangeable or uncontrollable ability or resulting from their hard-work and goal-setting, one representing a fixed mindset and the other a growth mindset (Horwitz, 1988; Wenden, 1998). A wide gap followed in the studies of language mindsets (LM) until 2010, when the general mindset framework (Dweck, 1999) was used by Mercer and Ryan to explore mindset among EFL learners (through interviews). This study provided evidence for the uniqueness of mindset in foreign language learning domain (e.g. benefiting from both entity and incremental mindset in language learning) (Lou & Noels, 2017).

Based on the main content of Dweck's (1999) original mindset framework and the qualitative results of Mercer and Ryan's (2010) work, three components of language mindset were revealed: general intelligence beliefs, second language aptitude beliefs, and age sensitivity beliefs about language learning. These three dimensions of language learning mindset and the two former categories of mindset (i.e. entity and incremental beliefs) comprised the basis of a framework to describe mindset in foreign language learning domain (Lou & Noels, 2017). The results of the related studies of mindset in EFL learning show that language learning mindsets are dynamic, situational, and socially embedded (Mercer & Ryan, 2010; Ryan & Mercer, 2011, 2012). Thus, Noels and Lou, the key scholars in foreign language mindset studies, planned to approach mindsets about language learning and its association with different motivational constructs via larger-scale works of research (Lou & Noels, 2016). These studies have been the primary attempts of operationalizing the construct in language learning domain.

EARLY PHASE OF LM MEASUREMENT

The first attempt to operationalize language mindset was made by Lou and Noels (2017) through the development of the Language Mindsets Index (LMI). The content was basically derived from Dweck's (1999) work in the math and intelligence domain as well as Mercer and Ryan's (2010) investigation of language learners' mindset. There are three sub-scales in the measurement instrument developed by Lou and Noels (2017). Six items enquired about fixed and growth beliefs about general language intelligence (GLB). Another six items explored second language learning beliefs (L2B), and six items to measure beliefs about the age sensitivity of language learning (ASB).

Lou and Noels (2017) ran confirmatory factor analysis (CFA) and confirmed six factors within the model, including fixed GLB, fixed L2B, fixed ASB, growth GLB, growth L2B, and growth ASB. Then, they conducted a second-order CFA to reduce the complexity of the structure more. They found that these six factors can be integrated in two, growth and fixed mindsets. The correlation between these two factors was high ($r = -.78$, $p < .001$). Therefore, they developed a composite language mindsets index by putting together the fixed and growth (reverse scored). As a result, a higher composite score pointed to a higher fixed mindset.

To validate LMI, the developers decided to test how well the scores on this tool went with language learners' written accounts of their language mindsets. Thus, in another work of research (Lou & Noels, 2017), 189 university students taking part in language classes filled out the index and responded to an open-ended question as well to explore their mindsets regarding language intelligence. The majority of the respondents referred to different aspects and beliefs, which led to a total of 376 codable responses. The final analysis indicated that learners as a group have different beliefs both types of mindsets (fixed and growth) can be found. Lou and Noels (2017) then tested the association between the respondents' scores on LMI and their written accounts. They ran one-way ANOVAs to check the mean differences on the index among the three groups of respondents who expressed fixed beliefs, growth beliefs, and both. The findings revealed that the respondents' extemporaneous written accounts matched adequately with the LMI scores. Therefore, the index managed to cover the respondents' expressed beliefs, adequately distinguishing those who held fixed mindsets, growth mindsets, or both.

Later on, Lou and Noels (2016) developed and tested a model of language learners' self-perceived language competence, goal orientations, fear of failure, decision to continue language learning, and reactions in failure conditions. The analysis of their conceptual path model was conducted in Mplus, and the final model showed to be fit. Language learners with a fixed mindset showed to be less likely to set a learning goal and reacted to failure with less mastery and lower motivation to continue language learning. They were also more afraid of failure in future. They found that perceived language competence accounted for a higher learning goal and a lower performance avoidance goal, as well as all reactions to failure. Lou and Noels (2016) were also interested in finding out whether it was possible to change language learners' mindset or not. They concluded that language learners can be encouraged to change their mindsets so as to influence their goal orientations and reactions to failure conditions, even with an apparently minor intervention such as a magazine article.

Dynamic phase of language mindsets measurement

Regardless of the results of the above studies focusing on foreign language mindset, two relevant issues are raised here, one about the validity of the instruments used to measure language mindsets and the other the research methodological designs to capture LM. Concerning the former, the issue is whether the existing instrument manages to measure changes of LM over time, which, as addressed in the measurement studies of the construct was admittedly dynamic and changeable. The latter question deals with how single-shot measurements can address the longitudinal nature of language mindsets.

In fact, what is commonly missing in the domain-specific measurement of mindset is the neglect of the validation of the construct over time. Simple exploratory, confirmatory factor analysis, principal component analysis or other conventional statistical procedures were applied to measure the construct validity of the instrument. It appears that the existing measurement instrument has been incapable of capturing the growing nature of LM. The other issue concerns the research design (i.e. how the measurement instrument is planned to be used to measure what it is supposed to). To address this matter, we should see what best fits the exploration of personality constructs in the field of SLA.

As maintained by Gass and Plonsky (2020), SLA domain is dynamic and takes advantage of a developing range of methodologies elaborated in numerous publications indicative of a methodological turn in this field. Also, the ongoing changes overtime challenge scholars in this domain as they as they are supposed to embrace this longitudinal orientation in their research (see Elahi Shirvan, Lou, & Taherian, 2021). Yet, conventional research methods fail to capture this orientation as it needs to be addressed via advanced methods such as latent growth modeling (LGM) (Hiver & Al-Hoorie, 2019), enabling researchers to trace the growth path in a psychological construct. If more than one psychological construct is aimed to be examined longitudinally, either a composite LGM or a curve-of-factors model (CFM) (McArdle, 1988), also known as a second-order LGM, can be used to deal with the issues involved in the use of composite variables in each time point of measurement in a univariate LGM. In other words, the CFM extends the univariate LGM via the incorporation of multiple constructs at each time point (Whittaker, Beretvas & Falbo, 2014).

The LCFA-CFM approach to Dynamics of language mindsets

Exploring changes in psychological constructs can be conducted through different classic research methods such as mean comparisons and repeated-measures analysis of variance. Nevertheless, the emergence of structural equation modeling (SEM) has helped researchers consider latent variables in such longitudinal explorations (Wickrama, Lee, O'Neal & Lorenz, 2016). Longitudinal confirmatory factor analysis (LCFA), a SEM based analytical approach, is an extension of a classic confirmatory factor analysis (CFA), which is generally used to confirm a hypothetical structure of a psychological construct. It indicates how different indicators or items measuring a number of sub-constructs load on the global construct. To measure changes of a construct over time, a simple CFA can be extended to an LCFA via repeated measures of the construct in different time points or measurement occasions. LCFA also enables longitudinal invariance measurement. That is, it enables researchers to test whether the indicators of a given psychological construct can contribute to the structure of the same construct in the same way over time (Hiver & Al-Hoorie, 2019; Wickrama et al., 2016). It should be noted that longitudinal invariance measurement is absent the validation endeavors of language mindsets. LCFA is the main assumption for conducting a second-order growth curve.

All growth curve models can be used to describe and analyze change in personal constructs over time. They not only indicate changes in the construct within time but also measure the rate of growth, referred to as slope, as well as the influence of initial status (referred to as intercept). A major advantage of CFM is that it considers second-order latent variables. That is, the slope and intercept are identified by the repeated measures. Nevertheless, in CFM, the factor scores of the latent variable in the model (CFA latent factors) are later applied as the indicators of a second order growth curve. In other words, in the LCFA-CFM, the main latent factors in LCFA shape the indicators of the slope and the intercept in CFM.

The suggested steps in the LCFA-CFM analytical approach to validate the LMI can be summarized as: the repeated measure of the trait and analyzing the changes through time which is consistent with the longitudinal nature of the trait of interest (i.e. LM) (Hiver & Al-Hoorie, 2019; Lorenz, Wickrama, & Conger, 2004; Wickrama et al., 2016), ensuring that the sub-construct indicators (i.e. fixed and growth mindsets) contribute to the repeated latent factor (LM) with a common structure over time (the role of LCFA) (Meredith & Horn, 2001; Wickrama et al., 2016), accounting for inter-individual variation of the latent factor (LM) (Whittaker et al., 2014; Wickrama et al., 2016), consideration of measurement errors and time-specific variance (Little, 2013; Wickrama et al., 2016), allowing for autocorrelations among manifest variables (indicators) (Little, 2013; Wickrama et al., 2016), secondary growth factors reflecting the temporal comorbidity of different sub-constructs (i.e. suggesting a latent factor explanation for the co-occurrence of sub-constructs) (Wickrama et al., 2016), and fitness to the CDST approach and line of research (Hiver & Al-Hoorie, 2019; Meredith & Horn, 2001; Thompson &Green, 2006).

The validation approach through LCFA-CFM occurs in four stages (as suggested by Wickrama et al., 2016) including 1) testing the longitudinal correlation patterns between indicators of the latent factor, 2) estimating a configural (unconstrained) LCFA with the help of indicators and including the autocorrelations of errors, 3) ensuring measurement invariance of the factor loadings, mean parameters and the error variance of the indicators between and among the points of times, and 4) estimation of the CFM through the latent factors of the LCFA detected for the measurement model. It is worth noting that the first three belong to the LCFA and the last step is associated with the CFM. The former involves with the first-order latent variables whereas the latter is linked with the second-order latent variables.

Measuring psychological constructs like language mindsets from a longitudinal perspective needs to be conducted by appropriately validated measurement instruments which can capture the temporal changes of the construct of interest. The present research aimed to suggest a longitudinal confirmatory factor analysis-curve of factors model to validate the only domain specific measurement instrument for LM. To this aim, the LMI developed and validated (through conventional statistical methods) by

Lou and Noels (2017) was used to collect data from a sample of 437 EFL learners in four points of time during their language learning experience. These data were used for the construct validation of the scale through LCFA-CFM approach.

The present study not only aimed to consider the limitations of classic statistical approaches in measuring the temporal aspects of LM but also tested its longitudinal construct validation. This research is the first study which measures the validity of LM over time and models the second-order latent factors related to the measurement of this construct. It not only reports on the patterns of change in L2 learners' fixed and growth mindsets through time, but also measures the rate of change in their overall mindset and the link of the initial status on L2 learners' mindset with their rate of growth in this construct. With these points in mind, we aimed to answer the following research questions:

1. Is the language mindsets index psychometrically valid for measuring language learners' mindsets over time?
2. To what extent can the initial level of language mindsets reflect the growth level of the construct over time?

METHOD

The present quantitative study employed a LMI measurement instrument developed by Lou and Noels (2017). However, its validity was supposed to be tested longitudinally. The latent construct explored as self-reports was LM which was made up of two sub-constructs, fixed and growth mindsets. These two were measured along 18 items in the target scale. The required data were collected from a sample of 437 EFL learners in four phases of time to validate the scale along these four phases and measure the growth of the trait among individuals. The scale was validated via a statistical model subsumed under the SEM analytic framework. However, it was not among the traditional SEM methods that require cross-sectional data, but rather it involved longitudinal SEM analysis considered a newcomer to the SLA field of research (Hiver & Al-Hoorie, 2016). What follows is an introduction of the present participants, instrumentation and procedures.

Participants and setting

The research population benefiting from the LMI is EFL/ESL language learners. Among this population, 437 (278 females and 159 males) Iranian EFL learners were purposively selected from the private language schools of three big cities in Iran. These private language institutes provided English language courses from beginning to advanced levels of proficiency. One of these cities was located in the north, one in the center and the other in the east of Iran. Their language proficiency level ranged from lower-intermediate to upper-intermediate and their age ranged between 17 and 34. All the participants' first language was Persian. These students learned English as a foreign language. The data collection occurred in spring and summer, 2020.

Instrumentation

The measurement scale used in the present study to test language learners' mindset was the Language Mindsets Index (LMI) developed by Lou and Noels (2017). The content of this scale was in fact derived from Dweck's (1999) work in the math and intelligence domain as well as Mercer and Ryan's (2010, 2012) exploration of language learners' mindset. In this scale, there are three sub-scales in the measurement instrument developed by Lou and Noels (2017). Six items enquired about fixed and growth beliefs about general language intelligence (GLB) (e.g. to be honest, you can't really change your language intelligence). Another six items explored second language le beliefs (L2B) (e.g. It is difficult to change how good you are at foreign languages) and the others assessed beliefs about the age sensitivity of language learning (ASB) (e.g. People can't really learn a new language well after they reach adulthood). To test the reliability and validity of the instrument, 1,633 university students answered the LMI on a six-point Likert scale ranging from strongly disagree to strongly agree. The developers found that the multiple factors can be integrated in two, growth and fixed mindsets. Thus, they hypothesized three associated bipolar second-order factors (fixed and growth mindsets) which represented the three dimensions of language mindsets (GLB, L2B, and ASB). That is, six distinct dimensions (GLB-fixed, L2B,-fixed, ASB-fixed, GLB-growth, L2B-growth, and ASB-growth) are reflected in terms of two broad sets of linked mindsets, which represent fixed and growth mindsets. The association between these two factors was high ($r = -.78$, $p < .001$). Thus, they developed a composite language mindsets measure by putting together the fixed and growth. So, a better composite score pointed to a more fixed mindset. This composite version was used in the present study. For the purpose of the study, the translated version of the scale with a high estimated reliability ($\alpha = 0.91$) was used.

Data Collection

The required data to be analyzed longitudinally were collected online using the LMI developed by Lou and Noels (2017). The LMI with 18 items was provided to the target sample in four phases at two-week intervals initiated at the beginningof the EFL program (to account for the initial status factor). The present data collected longitudinally helped assess changes in the target variable overtime. It also helped estimate the rate of changes in each phase and took into account the inter-individual distinctions. Questionnaire completion was done sequentially in class in the presence of a member of the research team. The confidentiality of the information was ensured.

Data analysis

To conduct the required statistical analyses, Mplus 8.4 was used with a robust maximum likelihood estimator (MLR). At first, we checked the assumptions for conducting a CFA and LGM. Full information maximum likelihood was used to tackle the missing data. It was necessary to check the observed correlation matrix of the components (i.e. fixed and growth mindsets) so as to find evidence to whether the model fit the data structure or not. As suggested by Little (2013), a LCFA model is suitable when the correlation coefficients among sub-construct indices of the primary latent variable at the same point of time are higher than the association of the same indices at various points of time, or autocorrelations. So, we mapped the correlation matrix between components to provide evidence for the existence of our latent variable (i.e. LM). Then, we examined the longitudinal relationships among the latent variable via an unconstrained LCFA model (i.e. a configural model). The factor loading (λ) of one indicator was set as 1 at each point of time, and its intercept was considered zero for model identification purposes (regarded as the "marker variable" scale setting for CFA parameters). To test the model fit, we used goodness of fit indices including comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The acceptable range were CFI and TLI $\geq .90$ and $\geq .95$, and RMSEA and SRMR $\leq .08$ and $\leq .05$, attesting to sufficient and excellent fit indices, respectively (Hu &Bentler, 1999; Marsh, Hau, & Wen, 2004).

Later on, the standardized factor loadings for each component of LM (fixed and growth) which comprised the latent variable (LM) were calculated. Traditionally, in the factor analysis literature, factor loadings $\geq .60$ are considered acceptable (Matsunaga, 2010). Besides, the associations among the latent factors (i.e., LM over points of time) were estimated. The statistical significance of auto-correlated errors among specific subdomains was also tested. Afterwards, the measurement invariance was tested through a multiple indices. Initially, we fit a configural factorial invariance model. With this unconstrained model, we saw whether each latent variable could be formed in a similar fashion. Then, a weak invariance model was calculated.

Next, a strong invariance model was estimated. If the fit indices proved that the strong invariance model was not similar to the weak invariance model, we could not assume that the LCFA could account for the longitudinal variations of true means because may be a change in the LM mean through time was due to the variability in the means of observed variables through time. In order to test each type of measurement invariance, the overall model fit indices were checked, including $\Delta\chi2$ and ΔCFI. In case the assumption of measurement invariance was met for the LCFA model, we estimated the second-order growth curve modeling (CFM).

RESULTS

The multiple phases of running LCFA-CFM, as recommended by Wickrama et al. (2016) include "testing the longitudinal correlation patterns between indicators (of the latent factor)", "estimating a configural (unconstrained) LCFA with the help of indicators and including the autocorrelations of errors", "ensuring measurement invariance of the factor loadings, mean parameters and the error variance of the indicators between and among the points of times" and "estimating the CFM using the latent factors of the LCFA that has been identified for the measurement model". Then, the results are provided here in these four steps.

Step One: Investigating the longitudinal correlation patterns among indicators (subdomain manifest variables)

In advance to performing a LCFA, Wickrama et al. (2016) recommend examining the observed correlation matrix of the subdomain indicators so as to obtain evidence as to whether, generally, the model fits the data structure. Little (2013) suggested that a LCFA model is appropriate when the correlation coefficients among subdomain indices of the global latent domain in the same point of time are higher than the correlation coefficients among the same subdomain indices at different points of time, or autocorrelations. Table 1 shows an observed correlation matrix of indices for two subdomains over time. Associations among the two subdomain indicators (i.e. fixed and growth mindsets) at the same occasion are high. More specifically, these correlation coefficients range between.68 and.73. The correlations for the same subdomain at the different time points (autocorrelations) are lower and range from .21 to

Table 1. Correlation Matrix between Subdomains

	Fixed mindset				Growth mindset			
	Fixed 1	**Fixed 2**	**Fixed 3**	**Fixed 4**	**Growth 1**	**Growth 2**	**Growth 3**	**Growth 4**
Fixed 1	-							
Fixed 2	.37	-						
Fixed 3	.34	.36	-					
Fixed 4	.23	.21	.47	-				
Growth 1	.73	.54	.51	.49	-			
Growth 2	.51	.71	.44	.46	.51	-		
Growth 3	.56	.54	.68	.48	.28	.42	-	
Growth 4	.53	.51	.54	.72	.31	.33	.49	-

Note: Fixed: Fixed language mindset Growth: Growth language mindset

.47 for fixed mindset, .28 to .51 for growth mindset, (see the coefficients within boxes).

The large correlation coefficients between the two indicators (i.e., fixed mindset and growth mindset) at the same time point provide evidence for the existence of a global latent factor, or global domain, for each of the 4 points of time. We refer to this global latent domain as language mindsets.

Step Two: Performing an Unconstrained Longitudinal Confirmatory Factor Analysis (LCFA)

After testing the longitudinal correlation pattern among indicators, the next step is to test the longitudinal relationships among the global latent factor domain through an unconstrained LCFA model (a configural model).The factor loading (λ) of one index was set to 1 for every time point (Fixed~4), and its intercept was set at zero for model identification (this is regarded as "marker variable" scale setting for the CFA parameters).

The results of the initial LCFA model indicate that the model adequately fit the data structure ($\chi 2$(df) = 298.144 (82), p < .05; CFI/TLI = .947/.937; RMSEA = .048; SRMR = .052).

As shown in Table 3, the standardized factor loadings for every subdomain manifest variable (e.g., fixed and growth) comprising the global latent domain (i.e., Language mindsets) were .72 [for fixed mindset] and .76 [for growth mindset] at Time 1, .70[for fixed mindset] and .72 [for growth mindset] at Time 2, .81[for fixed mindset] and .86[for growth mindset] at Time3, and .80[for fixed mindset] and .89 [growth mindset] at Time 4. Conventionally, according to the related literature on factor analysis, factor loadings ≥ .60 are deemed acceptable (Matsunaga, 2010). Thus, these factor loadings seem to be acceptable and suggest that together these two specific factors are indicators of latent factors of language mindsets.

Moreover, the associations among the latent factors (i.e., language mindsets through time) lie in a moderate range (from .41to .56, p < .001), which indicates modest correlations among the latent global factors (or acceptable discriminant validity of language mindsets through time) (see Table 2). Most of the autocorrelated errors between particular subdomains were statistically significant and in the expected direction (ranged from .21 to .42 for fixed mindset, .28 to .42 for growth mindset) even after

Table 2. Standardized Parameter Estimates of a Configural LCFA Model

	Estimate	S.E.	Est./S.E.	Two-Tailed p-value
Mindset1 by Fixed1	.81	.019	42.63	0.000
Mindset1 by Growth1	.84	.022	38.18	0.000
Minset2 by Fixed2	.79	.019	41.57	0.000
Mindset2 by Growth2	.83	.029	46.37	0.001
Mindset3 by Fixed3	.83	.018	28.62	0.000
Mindset3 by Growth3	.88	.027	30.34	0.000
Minset4 by Fixed4	.82	.021	39.04	0.000
Mindset4 by Growth4	.84	.025	33.62	0.000
Mindset1 with Mindset 2	.56	.026	21.23	0.000
Mindset1 with Mindset 3	.46	.028	16.42	0.000
Mindset1 with Mindset 4	.38	.027	14.07	0.000
Mindset2with Mindset 3	.53	.033	16.06	0.002
Mindset2with Mindset 4	.42	.031	13.54	0.000
Mindset3 with Mindset 4	.55	.027	20.37	0.000
Fixed1 with Fixed2	.30	.054	5.55	0.000
Fixed1 with Fixed3	.18	.041	4.39	0.000
Fixed1 with Fixed4	.16	.032	0.50	0.000
Fixed2 with Fixed3	.31	.047	6.59	0.000
Fixed2 with Fixed4	.24	.038	6.31	0.000
Fixed3 with Fixed4	.22	.041	5.36	0.000
Growth 1 with Growth2	.42	.071	5.91	0.000
Growth 1 with Growth3	.31	.070	7.75	0.002
Growth 1 with Growth4	.28	.061	4.59	0.000
Growth 2 with Growth3	.34	.062	5.48	0.001
Growth 2 with Growth4	.28	.058	4.82	0.00
Growth 3 with Growth4	.40	.059	6.77	0.001

controlling for the correlations between the latent factors of LM at various time points. These statistically significant autocorrelated errors among within-subdomain indicators imply the existence of certain trait-specific factors.

Step Three: Measurement Invariance of the LCFA Model

Under maximum likelihood (ML) estimation, measurement invariance is typically tested via a nested chi-square difference test, $\Delta\chi 2$, between the unconstrained model and the model(s) applying equality constraints (Ferrer, Balluerka, &Widaman, 2008; Harring, 2009). However, in a Monte-Carlo simulation research project, Meade, Johnson, and Braddy (2008) found that the $\chi 2$ statistic is very sensitive to sample size. Thus, for model comparison, the use of an alternative fit index was recommended, such as the comparative fit index (CFI), which is less sensitive to sample size and more sensitive to a lack of invariance than the $\chi 2$ statistic. Cheung and Rensvold (2002) suggested that the assumption of measurement invariance is met if the difference in the CFI (ΔCFI) between the unconstrained model and the constrained model is less than .01. However, Little (2013) suggests that the conclusion should not be based on any single statistic. Instead, multiple indices of the change in model fit should be considered simultaneously. Thus, here several model fit indices were considered when assessing measurement invariance. Table 3 shows the findings related to the nested model comparisons.

The analyses revealed that the configural model, or the unconstrained model (M2), has an acceptable overall fit. Then, we made M3 by constraining the factor loadings as equal. We tested the assumption of weak invariance by comparing M3 with M2. The findings indicated that the constraints included in M3 do not dramatically reduce the model fit compared to M2 (the configural model) ($\Delta\chi 2$ (df) = 32.837, p = .04; ΔCFI = .002). Therefore, the assumption of weak invariance is met.

We compared M3 (the weak invariance model) withM4 (the strong invariance model) that adds constraints to make the manifest variable means equal across time. The $\Delta\chi 2$ statistic indicated a statistically significant decrease in model fit ($\Delta\chi 2(7)$ = 11.461, p < .005; ΔCFI = .001), which suggests M3 is the best fitting model. Because Cheung and Rensvold (2002) showed that the set of constrained parameters is fundamentally the same across time when the ΔCFI is less than or equal to .01, we could proceed with the understanding that the strong measurement invariance can be assumed.

At last, we also checked for the strict invariance model. As anticipated, according to the previous models, the fit statistics indicated that strict invariance could not be assumed ($\Delta\chi 2$(df) = 37.127, p < .001; ΔCFI = .023). Wickrama et al. (2016) suggested that strong invariance, like we found support for in M5, is the least level of measurement invariance needed for proceeding to second-order modeling. That is, second-order modeling requires: (a) stable relationships between the factor loadings and the latent construct over time and (b) the ability to attribute "true mean" changes in the constructs over time to true construct differences and not to represent mean changes.

Step four: Estimating a Second-Order Growth Curve: A Curve-of-Factors Model (CFM)

Because the assumption of measurement invariance was met in the LCFA model, a second-order growth curve model was estimated, such as a curve-of-factors model (CFM). Probably, we can estimate the variance of the slope factor for the second-order growth curve model when diagonal covariances among indicators (here, adjacent covariances between language mindsets$_t$ and language mindsets$_{t+1}$) are higher than off-diagonal covariances.

In the present LCFA model with strong invariance, we realized that the covariances between adjacent latent constructs were higher (ranging between .53 and .56, p < .001) than the off-diagonal covariances (ranged from .38 to .46, p < .001). Such model covariances imply that a second-order slope variance may probably be estimated in a CFM without resulting in a solution that contains a negative variance.

The CFM results are represented in Figure 1. As shown by the model fit indices, the specified CFM was adequately fit with the data structure ($\chi 2$(df) = 743.612, p < .001; CFI/TLI = .977/.968; RMSEA=.044, SRMR = .046). The mean levels of the intercept and

Table 3. Results of Models Testing Measurement Invariance in LM Longitudinal CFA Model

	X^2	Model comparison	ΔX^2	CFI	ΔCFI	RMSEA (90% CI)	SRMR	BIC
Null model (M1)	738.986							
Configural LCFA model (M2)	156.814			.971		.071 (.022,.069)	.047	3236.263
LCFA with weak invariance (M3)	189.651	M3 vs. M2	32.837***	.969	.002	.052 (.028,.072)	.051	3228.112
LCFA with strong invariance (M4)	201.112	M4 vs. M3	11.461***	.968	.001	.058 (.042,.074)	.056	3223.481
LCFA with strict invariance (M5)	238.329	M5 vs. M4	37.127***	.945	.023	.062 (.052,.077)	.061	3219.613

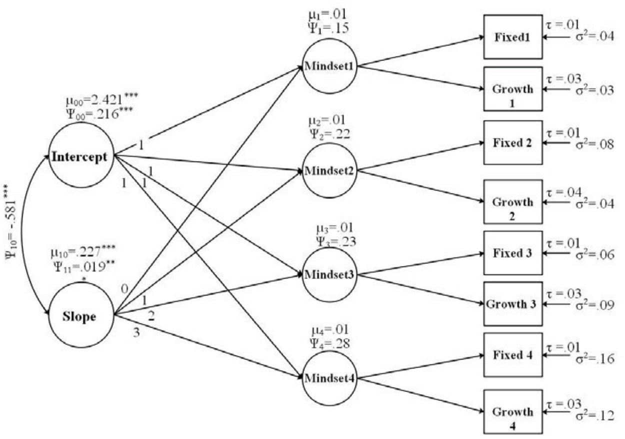

Figure 1. A Second-Order Growth Curve Model (CFM) from a Marker Variable Scale Setting Approach. Note: Unstandardized coefficients are included. Fixed= fixed language mindsets. Growth= Growth language mindsets. Strong invariance was specified via the marker variable approach. The residual variances among the same indicators over time along with the covariates among subdomains were associated but are not represented in the figure for simplicity. ($\chi 2$(df) = 743.612, p < .001; CFI/TLI = .977/.968; RMSEA = .044, SRMR = .046). *** p < .001.

slope of the second-order model were statistically significant, indicating an initial level of LM that is greater than zero and an increasing trend in LM over time (intercept: 2.421 p < .001, linear slope:.227, p < .001, respectively). Inter-individual differences in the second-order growth factors were also statistically significant, and the estimated variances proved the existence of inter-individual variation in both the second-order intercept (initial level) and the slope of change over time (intercept:.216, p < .001, slope: .019, p < .001). The statistically significant slope variance suggests that a number of individuals had a higher rate of variation in LM than others with a lower rate of variation in the construct over time. There were also others who kept the same level of LM over time.

Moreover, as represented in Figure 1, the negative covariance between the intercept and slope (r = -.581, p <.001) showed that lower initial scores in students' LM showed a steeper changeover time. Thus, those students who began at a higher level of LM also show less change in the trait through time and those participants who began at lower degree of LM showed more change in the trait throughout the program).

DISCUSSION

This study attempted to measure the temporal changes and development of foreign language mindset (LM) in multiple phases of an EFL course. The longitudinal approach it employed distinguishes this investigation from a body of related literature in the earlier phase of LM measurement (Dweck, 1999; Lou & Noels, 2016; Mercer & Ryan, 2010, 2012). These studies used conventional statistical procedures to measure the construct including PCA and simple CFA. Yet, what is commonly believed in the majority of the aforementioned related literature (those conducted in the 21st century) as well as the present study is that people's mindsets in the language area can be more complicated than in other areas, as how individuals come to know about their ability to learn languages usually entails multiple beliefs (Lou & Noels, 2020; Mercer & Ryan, 2009). Furthermore, in alignment with Lou and Noels (2020), the present findings showed that EFL learners had domain-specific mindsets about language learning. That is, a participant with a growth mindset about the certain language skills (i.e. reading and speaking) had a fixed language mindset about some other skill (i.e. writing).

The present study emphasized that LM needs to be investigated from a dynamic approach. Similarly, Lou and Noels (2020) pinpointed that relating language mindsets investigations to broader SLA research can help us better learn about the multifaceted and dynamic nature of mindsets in the growth of new languages. An evident relation is that language mindsets are particular kinds of language beliefs. Explorations of language beliefs have provided an important theoretical and practical domain for complex dynamic approaches (e.g., Barcelos & Kalaja, 2011). For instance, applying different methods (e.g., ethnography, longitudinal studies, idiodynamic approaches) can enrich the understanding of when and how changes in language mindsets happen and how they grow through time (Lou & Noels, 2020). Altogether, researchers from different approaches can contribute to the research sphere on language mindsets.

Part of the present findings showed inter-individual differences in the second-order growth factors which were also statistically significant with estimated variances pointing to the existence of inter-individual variation within both the second-order intercept (initial level) and the speed of change through time (slope) (intercept:.216, p < .001, slope: .019, p < .001). This result is in agreement with a body of research attesting to the malleability (dynamicity) of language mindsets. For one, Robins and Pals (2002) maintained that although mindsets are often approached as relatively fixed, trait-like beliefs that differ among individuals, they can also change within an individual through time and in different contexts. Similarly, there is evidence that test-retest correlations of language mindsets throughout a one-month period are strong yet not perfect (r2s = .50 and .56; Lou & Noels, 2017) and that priming students' mindsets can shift individuals' mindsets relatively (Lou &Noels, 2016; Dweck, 2006; Molway & Mutton, 2019).Similarly, Wilson and English (2017) pinpointed that mindsets can be regarded as context-based beliefs that can vary contingent on contextual specificities. The dynamic and situational aspects of mindsets, as described by Lou and Noels (2020), show that the development of mindsets involves social and interpersonal processes, having significant implications for teaching practices and interventions.

As the present findings showed, we can claim that the subdomain indices of the LMI, fixed and growth mindsets, account for the repeated latent factors which represent the global factor of LM with a common structure, showing the same meaning through time, and the factor structure including the factor loadings of both fixed and growth mindset is invariant through time. That is to say that the association between the indicators of fixed and growth mindset, as the subdomains of LMI, and the global factor of LM, has not changed across the four times points explored in this research. Thus, we can be confident that the findings of evaluating the actual variation of fixed and growth mindsets are not biased. Regardless of LCFA of the LMI, as dealt in this study, any observed variation in the construct in a language learning program might be misunderstood.

The CFM results indicated that the initial level of L2 students' LM was negatively correlated with the rate of LM growth within the program. The LM of those whose initial level of the trait was lower (i.e. they had a higher growth mindset) at the beginning grew dramatically faster than others whose initial degree of LM was higher (i.e. those with a more fixed mindset). This would point to the fact that an initial level of a personality trait does not guarantee the speed of change in the intensity of the trait within time. That would be why an approach like CFM is necessary to explore LM longitudinally in several points of time and not just once. This result proves Hiver and Al-Hoorie's (2019) attempts to draw attention to the essentiality of creative research methods especially advanced statistical techniques including CFM to deal with the dynamic nature of human traits and performance.

Multiple factors can be involved in the different rate of changes in the LM of L2 learners with an initially high or low level of the trait. A key factor raised in the literature is L2 learning motivation, as mindset is viewed as a motivational phenomenon (Dweck, 2006; Dweck & Leggett, 1988). As mentioned previously, in the present findings, language learners who had a higher growth mindset at the initial stage of the program experienced more fluctuations at a faster rate until the end of the program. A higher language growth mindset at the beginning of the course implies stronger beliefs in one's ability of learning the language through strategy and efforts (Lou & Noels, 2020). Thus, it is very well expected that those who begin the course with a growth mindset to language learning, show more internal motivation and self-initiated efforts to better learn the language (Lou & Noels, 2020). Learners with a more fixed mindset perceive the ability to learn a language as fixed and hardly changeable (Lou & Noels, 2016, 2020). Therefore, they are expected to benefit more from external motivators (e.g. teacher's encouraging role) than internal motivators to show changes in these beliefs toward language learning. This motivation can be influenced within the interpersonal system (i.e., the micro system). For instance, students can enrich their beliefs about language learning through contact with their learning materials, teachers, and peers (Haimovitz & Dweck, 2016), or they can be significantly influenced by their teacher. How teachers respond to students' achievement and failure may also push students to grow various mindsets (Lou & Noels, 2020).

Of note is that, in the dynamic setting of an L2 class, a number of relevant variables can act together to encourage language learners with a rather fixed mindset (at the opening of the program) to gradually see themselves able to learn the language and perceive their language learning practices rewarded. More research can help to show more about the variables influencing and influenced by L2 learners' mindset in the dynamic sphere of an L2 class. For example, more advanced types of curve growth modeling can also be employed to take into account more latent variables in the model such as motivation and mindset. Longitudinal SEM analyses create the chance to trace LM (and other similar personality traits) in the actual learning and show more about the interconnected network of learner-based and situation-specific variables.

CONCLUSION

Influenced by the trend of positive psychology in recent years, the present study managed to measure the nuanced changes in LM in a longitudinal study ensuring the measurement invariance over time and sensitivity to the initial status of the trait and the slope of change. LM has shown to be an effective personality trait learners experience in language learning and its exploration as well as other classroom emotions are significant predictors of students' performance. More importantly, the present study helped to enrich the picture of the cognitive pathway L2 learners take in different temporal stages of a language course and provided evidence for individual differences in the changing growth of LM experienced during the L2 course. It further showed that the initial level of the construct cannot reflect the intensity of LM learners experience in later stages of the FL course. Learner variables such as motivation as well as teacher's role in empowering learners to feel capable of learning and creating a positive and supportive environment can affect the development of the construct in L2 learners. Regarding the pedagogical implication of these findings, language teachers should not limit the assessment of their learners' language mindsets to just one session (e.g. the initial session of the course). Rather, they should see their learners' mindsets as a dynamic construct which can be developed toward growth mindsets over time. Thus, language teachers can consider developing suitable interventions or use innovative strategies to shift their learners' language mindsets from fixed ones to incremental ones.

The present study also drew attention to the need for substantiating the longitudinal validity of the scales measuring emotions in SLA domain. Considering the dynamic and developmental nature of learners' emotions such as LM, any measurement of the trait in single-shot research designs fails to capture the nuances of change in the trait during the language learning experience. Robust innovative statistical procedures such as the LCFA-CFM modeling employed in the present research help to measure the inherent dynamicity of the emotion as it is experienced in the reality of classroom learning. Further investigations can incorporate a variety of negative and positive L2 classroom-related constructs in this mediation model and compare their different effects.

REFERENCES

Barcelos, A. M. F., & Kalaja, P. (2011). Introduction to beliefs about SLA revisited. *System*, 39, 281– 289.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling,* 9, 233–255.

Dörnyei, Z., & Ushioda, E. (Eds.). (2009). *Motivation, language identity and the L2 self.* Bristol, UK: Multilingual Matters.

Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development.* Philadelphia: Taylor & Francis.

Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological Inquiry,* 6, 267-285.

Dweck, C.S., & Leggett, E.L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95*(2), 256-273.

Elahi Shirvan, M., Lou, N. M., & Taherian, T. (2021). Where do language mindsets come from? An ecological perspective on EFL students' mindsets about L2 writing. *Journal of Psycholinguistic Research*, *50* (5), 1065-1086.

Ferrer, E., Balluerka, N., &Widaman, K. F. (2008). Factorial invariance and the specification of second-order latent growth models. *Methodology, 4*(1), 22-36.

Gardner, R.C. (2010). *Motivation and second language acquisition: The socio-educational model.* New York: Peter Lang.

Gass, S., &Plonsky, L. (2020). Introducing the SSLA methods forum. *Studies in Second Language Acquisition*, *42*, 667-669.

Haimovitz, K., & Dweck, C. (2016). Parents' views of failure predict children's fixed and growth intelligence mind-sets. *Psychological Science*, *27*(1), 859-869.

Harring J. R. (2009). A nonlinear mixed effects model for latent variables. *Journal of Educational and Behavioral Statistics, 34*(3), 293–318.

Hiver, P., & Al-Hoorie, A. H. (2019). *Research methods for complexity theory in applied linguistics*. Bristol, UK: Multilingual Matters.

Hong, Y., Chiu, C., Dweck, C. S., Lin, D., & Wan, W. (1999). Implicit theories, attributions, and coping: A meaning system approach. *Journal of Personality and Social Psychology*, 77, 588– 599.

Horwitz, E. K. (1988). The beliefs about language learning of beginning university foreign language students. *Modern Language Journal, 72* (1), 283– 294.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford.

Lorenz, F. O., Wickrama, K. A. S., & Conger, R. D. (2004). Modeling continuity and change in family relations with panel data. In R. D. Conger, F. O. Lorenz, & K. A. S. Wickrama (Eds.), *Continuity and change in family relations: Theory, methods, and empirical findings*, (pp. 15–62). Mahwah, NJ: Erlbaum.

Lo Lou, N. M., & Noels, K. A. (2016). Changing language mindsets: Implications for goal orientations and responses to failure in and outside the second language classroom. *Contemporary Educational Psychology*, *46*(1), 22-33

Lou, N. M., & Noels, K. A. (2017). Measuring language mindsets and modeling their relations with goal orientations and emotional and behavioral responses in failure situations. *The Modern Language Journal*, *101*(1), 214-243.

Lou, M. & Noels, K. A. (2019). Promoting growth in foreign and second language education: A research agenda for mindsets in language learning and teaching. *System*, *86*. 102126.

Lou, N. M., & Noels, K. A. (2020). Mindsets about language learning and support for immigrants' integration. *International Journal of Intercultural Relations*, *79*(1), 46-57.

MacIntyre, P. D., Mercer, S., &Gregersen, T. (2020). *Complexity perspectives on researching language learner and teacher psychology*. Bristol, UK: Multilingual Matters.

Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural Equation Modeling, 11*(3), 320-341.

Matsunaga, M. (2010). How to factor-analyze your data right: Do's don'ts, and how-to's. *International Journal of Psychological Research*, *3*(1), 97-110.

McArdle, J.J. (1988). Dynamic but structural equation modeling of repeated measures data. In: Nesselroade, J.R., & Cattell, R.B. (Eds.), *Handbook of multivariate experimental psychology* (pp: 561-614). New York, NY: Plenum Press.

Meade, A., Johnson, E., &Braddy, P. (2008). Power and sensitivity of alternative fit indices in tests of measurement invariance. *The Journal of applied psychology*, *93*(2), 568-92.

Mercer, S., & Ryan, S. (2010). A mindset for EFL: Learners' beliefs about the role of natural talent. *ELT Journal,* 64, 436-444.

Meredith, W., & Horn, J. (2001). The role of factorial invariance in modeling growth and change. In A. Sayer & L. Collins (Eds.), *New methods for the analysis of change* (pp. 203–240). Washington, DC: American Psychological Association.

Molway, L., & Mutton, T. (2020). Changing mindsets in the modern foreign languages classroom: an intervention combining intelligence theories and reading strategies. *The Language Learning Journal*, *48*(5), 598-612.

Robins, R., & Pals, J. (2002). Implicit self-theories in the academic domain: Implications for goal-orientation, attributions, affect, and self-esteem change. *Self and Identity*, *1*(4), 313-336.

Ryan, S. & Mercer, S. (2011). Natural talent, natural acquisition, and study abroad: Learner attributions of agency in language learning. In G. Murray, X. Gao & T. Lamb (Eds.), *Identity, motivation and autonomy in language learning* (pp. 160–176). Bristol, UK: Multilingual Matters.

Ryan, S. & Mercer, S. (2012). Implicit theories: Language learning mindsets. In S. Mercer, S. Ryan, & M. Williams (Eds), *Psychology for language learning: Insights from research, theory, and practice* (pp. 74–89). Basingstoke, UK: Palgrave Macmillan.

Thompson, M. S., & Green, S. B. (2006). Evaluating between-group differences in latent means. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (pp. 119–169). Greenwich: CT: Information Age.

Wenden, A. (1998). Metacognitive knowledge and language learning. *Applied Linguistics*, *19*(1), 515-537.

Whittaker, T. A., Beretvas, S. N., & Falbo, T. (2014). Dyadic curve-of-factors model: an introduction and illustration of a model for longitudinal non-exchangeable dyadic data. *Structural Equation Modelling, 21*(2), 303-317.

Wickrama, K. A. S., Lee T. K., O'Neal C. W. & Lorenz, F. O. (2016). *Higher-order growth curves and mixture modeling with Mplus.* New York: Routledge.

Wilson, A., & English, J. (2017). The motivated fluidity of lay theories of change. In *The Science of Lay Theories* (pp.17-43). Springer, Cham.