Article History
Received: 23.11.2022
Received in revised form: 02.05.2023
Accepted:06.06.2023
Article Type: Research Article

International Journal of Contemporary Educational Research (IJCER)

www.ijcer.net

Latent trajectories of subjective well-being: An application of Latent Growth Curve and Latent Class Growth Modeling

Esra Sözer Boz[1], Nilüfer Kahraman[2]
[1]Bartin University, 0000-0002-4672-5264
[2]Gazi University, 0000-0003-2523-0155

To cite this article:

Sözer-Boz, E. & Kahraman, N. (2023). Latent trajectories of subjective well-being: An application of latent growth curve and latent class growth modeling. *International Journal of Contemporary Educational Research, 10*(2), 411-423. https://doi.org/10.52380/ijcer.2023.10.2.308

IJCER International Journal of Contemporary Educational Research
Volume 10, Number 2, June 2023, Page 411-394 ISSN: 2148-3868

Latent Trajectories of Subjective Well-Being: An Application of Latent Growth Curve and Latent Class Growth Modeling**

Esra Sözer Boz[1*], Nilüfer Kahraman[2]
[1]Bartin University
[2]Gazi University

Abstract

This study proposed a three-stage measurement model utilizing the Latent Growth Curve Modeling and Latent Class Growth Analysis. The measurement model was illustrated using repeated data collected through a four-week prospective study tracking the subjective well-being of volunteer college students (*n*=154). Firstly, several unconditional growth models were estimated to define the model, providing a better representation of individual growth trajectories. Secondly, several conditional growth models were formulated to test the usefulness of covariate variables hypothesized to explain observed variance in growth factors. Finally, latent class growth models were estimated to further explore different latent trajectory classes. Results showed that students' subjective well-being changed over time, and the rate of this change and its covariates were not constant for the entire sample. This study clearly illustrates how a longitudinal measurement approach can enhance the scope of findings and the depth of inferences when repeated measurements are available.

Keywords: Longitudinal, Individual differences, Latent growth curve modeling, Latent growth classes, Measurement design

Introduction

The most fundamental issue of educational research is determining how individuals' development occurs over time (Aşkar & Yurdugül, 2009). The development process has a multidimensional structure encompassing people's cognitive, affective, and psychomotor skills. Changes in these skills due to various causes result in various outcomes. Hence, one of the ultimate goals pursued by methodological studies in the educational sciences is to uncover general principles for measuring or monitoring the complex structure of individual development (Curran & Wirth, 2004). Repeated observations from longitudinal measurement design, including the time effect, are needed to analyze the change. The reason behind designing the research design as longitudinal rather than cross-sectional is the notion that measurements taken to cover a process can capture the structure of the feature in a more realistic way. In other words, if the structural change over time is theoretically supported, the practical significance of the results can be increased by supporting the measurements and statistical methods used with a longitudinal approach (Kane, 2013). A longitudinal measurement design provides essential information about intra-individual differences, inter-individual differences, and the sources of these differences (Duncan & Duncan, 2009).

Longitudinal research integrates three elements: a theoretical model of the structure, a measurement design that offers a distinct and comprehensive observation of the change process, and statistical models for data analysis (Collins, 2006). The interaction between theory, measurement design, statistical model, and the conclusions drawn from results to add to theory is a never-ending loop (Curran & Willoughby, 2003). Longitudinal research incorporating these three elements will provide an in-depth look at the complexities of individual development. This study focuses on examining intra-individual changes and inter-individual differences in scenarios where the construct is dynamic. The contributions of longitudinal measurement and statistical methods are provided through an example.

* Corresponding Author: *Esra Sözer Boz, esrsozer@gmail.com*
** This paper is derived from part of the doctoral dissertation entitled "Latent Growth Curve Modeling and Latent Class Growth Analysis: An Application of Prospective Subjective Well-Being" prepared by Esra Sözer.

It is necessary to analyze the data using appropriate statistical models to answer the research questions correctly (Hertzog & Nesselroade, 2003). Longitudinal statistical models significantly impact the combination of repeated measures, the analysis of change process hypotheses, and the validity of interpretations drawn from the conclusions. In recent studies, growth modeling has increased researchers' interest in analyzing the differences between change patterns and observation units over time. However, the educational sciences literature has limited application of growth modeling. In the present study, Latent Growth Curve Modeling (LGCM) (Meredith & Tisak, 1990) and Latent Class Growth Analysis (LCGA) (Nagin, 1999), constructed by merging growth model analysis with covariance analysis, were used to model individual growth trajectories.

The Framework of Latent Variable Models

LGCM and LCGA are classified as Latent Variable Models (LVMs) (Muthén, 2007). Within the theoretical framework of LVMs, Table 1 displays the statistical models classified according to the kind of latent variable and whether the research is cross-sectional or longitudinal. Quantitative changes can be explored when the latent variable is continuous (Ruscio & Ruscio, 2008). Factor Analysis can be used as a cross-sectional model, and LGCM can be used as a longitudinal model for examining quantitative changes. Qualitative differences can be investigated when the latent variable is categorical. Some latent variables are hybrid, with both continuous and categorical individual differences. In longitudinal models, LCGA and Growth Mixture Modeling (GMM) (Muthén & Shedden, 1999) are employed when the latent variable is categorical or hybrid.

Table 1. Latent variable models

	Latent Variables		
	Continuous	**Categorical**	**Hybrid**
Cross-sectional	Factor analysis	Latent class analysis	Factor mixture analysis
Longitudinal	Latent growth curve modeling	Latent class growth analysis	Growth mixture analysis

LGCM assumes that individuals come from a unique population and that an average growth trajectory can sufficiently estimate the population's growth. Also, it is assumed that covariate variables influence individuals similarly. However, the average growth trajectory alone is insufficient if the population of growth patterns contains subgroups, and the covariate variables affect these subgroups in various ways. While LGCM allows for the testing of subgroups in the context of observed group membership, such as gender and ethnicity (Curran & Wirth, 2004), it falls short of defining unobserved latent growth groups (Wang & Bodner, 2007). Unlike LGCM, GMM and its special type, LCGA, focus on characterizing unobserved heterogeneity (latent classes) in the population and classifying individuals with similar growth patterns (Jung & Wickrama, 2008).

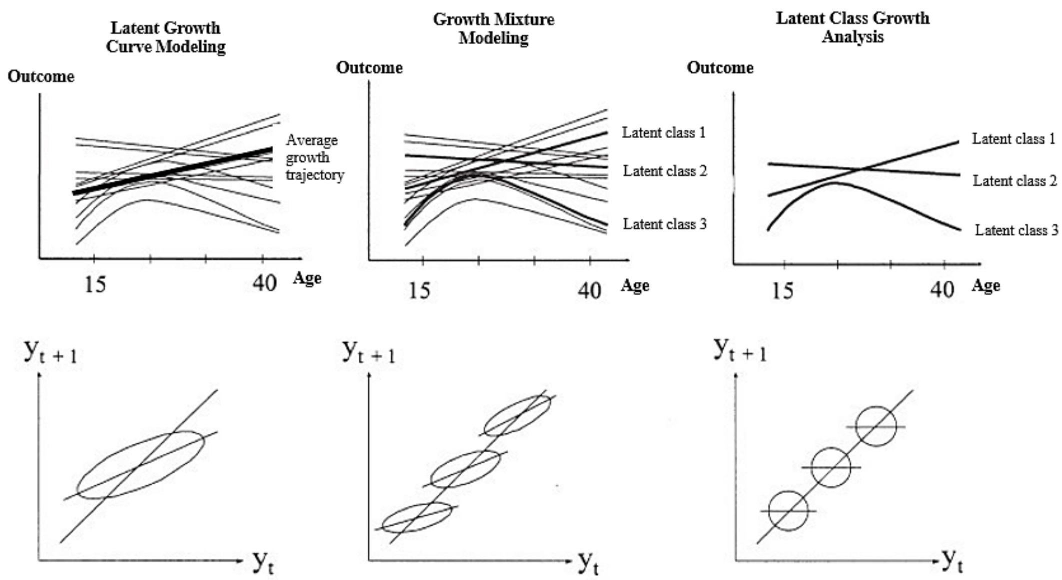


Figure 1. Growth modeling diagrams

Figure 1 illustrates the three major growth modeling approaches (Muthén, 2007). The growth is defined with continuous latent variables in LGCM, whereas the growth is defined with continuous and categorical latent variables in GMM and LCGA (Berlin et al., 2014). GMM allows the differentiation of growth trajectories among the latent classes and individual differences within each class (Jung & Wickrama, 2008). In LCGA, the variance and covariance values of the growth factors in each class are supposed to be constrained to zero and allowed to vary only across classes (Berlin et al., 2014; Nagin, 1999).

According to a study by Nylund et al. (2007), combining LGCM and LCGA will contribute to more in-depth studies and expand the validity and reliability of interpretations. LGCM and LCGA are commonly used to analyze changes in academic achievement (Bilir et al., 2008; Gottfried et al., 2016), health sciences (Aili et al., 2021), and sports sciences (Kim et al., 2016). The change in mental health throughout the COVID-19 pandemic was also investigated using longitudinal statistical models (Pierce et al., 2021). The purpose of the current study is to propose a longitudinal measurement method for describing the properties of individual growth trajectories. This method has been illustrated using data from a repeated four-week study on subjective well-being. The following research questions were examined:

(1) What is the shape of the average growth trajectory in the sample?
(2) When time-varying covariates are incorporated into the growth model, how do model comparisons provide results?
(3) How many latent classes best represent individual growth patterns?

Method

Research Design

This study was developed as a longitudinal panel design (Menard, 2008) with repeated measurements. The same settings and participants are included at each measurement time in this design, also known as cohort studies. Cohort studies can be prospective or retrospective. Prospective studies are carried out from the present into the future. This is a prospective cohort study.

Sample and Data Collection

It is necessary for the participants to be available and cooperative throughout the period to avoid data loss in longitudinal research. The observations of 154 university students who volunteered to complete the survey are included in the data gathered through repeated measures between the 2018 and 2020 academic years. Participants consisted of 76% female students and 17% male students.

The minimal requirement for longitudinal statistical models is that they must be measured at least three equal or irregular intervals. The measurement time points should be sensitive enough to identify the change meaningfully (Ployhart & Vanderberg, 2010). Collecting additional observations leads to higher precision for estimating the individual growth trajectory and greater reliability for measuring change (Willett & Sayer, 1994). Participants were asked to provide observations repeated every week at four equally spaced time points before the midterm exams in the 2018-2020 academic year. Time is coded as 0, 1, 2, and 3 in modeling a linear growth trajectory with four repeated observations. T_0 represents the initial time point; T_1 is the second; T_2 is the third; and T_3 is the fourth. The researcher administered online surveys to gather data from students.

Measures

The data comes from a more extensive longitudinal study asking how participants spent the previous week concerning various positive and negative affective factors. Participants were asked to rate these items on a 5-point Likert-type scale (1 = never to 5 = very often). Observed indicators such as happiness, peace, satisfaction, and energy were employed to measure the subjective well-being construct. Confirmatory Factor Analysis (CFA) was used to examine factor structures of subjective well-being over time. CFA results are given in Table 2.

Table 2. Results of the CFA for subjective well-being across measurement time points

	Measurement Time Points			
	Time 1 (T_0)	Time 2 (T_1)	Time 3 (T_2)	Time 4 (T_3)
AIC	2455.21	2397.86	2580.33	2462.39
BIC	2497.65	2440.31	2622.78	2504.83
CFI	1.00	0.98	0.98	0.99
TLI	1.00	0.96	0.94	0.98
RMSEA	0.00	0.10	0.10	0.10
SRMR	0.006	0.01	0.026	0.014
Cronbach α	0.87	0.89	0.87	0.89
McDonald ω	0.91	0.90	0.88	0.91

Table 2 shows that the CFA results confirmed the single-factor structure of subjective well-being across four-time points. Reliability coefficients of four-time points were between 0.87 and 0.89 for Cronbach's α and between 0.88 and 0.91 for McDonald's ω. The McDonald's ω coefficient is computed for composite total score reliability. Subjective well-being scores were calculated based on the total scores of the observed indicators. The total subjective well-being scores range from 4 to 20. Some variables, including sleep quality, resilience, and stress, were selected as covariate variables. Resilience and stress items are rated on a 5-point Likert-type scale (1 = never to 5 = very often), and sleep quality scores range from 5 to 20.

Data Analysis

Participants with missing values at any time point were excluded from the analysis. The descriptive statistics indicated a declining trend in the mean subjective well-being over the weeks ($X_{T0} = 11.9$; $X_{T1} = 10.9$; $X_{T2} = 10.2$; $X_{T3} = 10.0$). It is suggested that for a better estimation of LGCM, the slope parameter must have adequate variance (Lorenz et al., 2004). Pearson product-moment correlations were calculated to evaluate the variance of the slope parameter. The correlations between four-time points showed that the first and second-time points ($r = 0.50$, $p < 0.01$) had a stronger relationship than the first and third-time points ($r = 0.30$, $p < 0.01$). This correlation means that later measures have progressively lower correlations with earlier measures as a function of increasing time. This result suggests that the rate of change over time varies and there is an inter-individual variance in the rate of change.

Latent Growth Curve Modeling

LGCM consists of two parts: a measurement model and a structural model. The measurement model refers to the intra-individual level. The measurement model part is:

$$y_{it} = \eta_{0i} + \eta_{1i}a_t + \eta_{2i}a^2{}_t + \varepsilon_{it} \quad (1)$$

where y_{it} is the observed outcome measure of participant i at the time point t; η_{0i}, η_{1i}, and η_{2i} are the intercept, linear slope, and quadratic slope, respectively, for participant i; ε_{it} is the error score for participant i; and a_t is the associated time score. Time scores are coded 0 for the initial time point, so the slope is interpreted as the rate of change, and the intercept is interpreted as the mean score at the initial time point. The intercept and slope parameters are growth factors in the model. The quadratic slope will be removed from the model if it is not statistically significant. The structural model parts are:

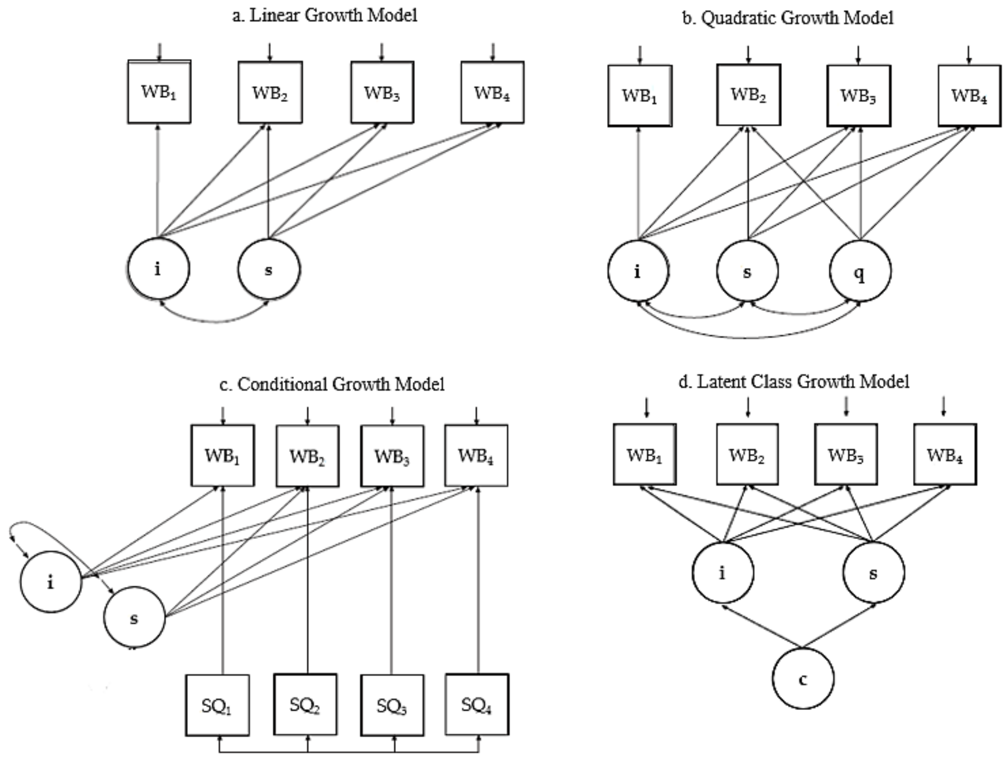
$$\begin{aligned} \eta_{0i} &= \beta_{00} + \beta_{01}x_i + \zeta_{0i} \\ \eta_{1i} &= \beta_{10} + \beta_{11}x_i + \zeta_{1i} \\ \eta_{2i} &= \beta_{20} + \beta_{21}x_i + \zeta_{2i} \end{aligned} \quad (2)$$

where β_{00}, β_{10}, and β_{20} are the mean intercept, the mean linear slope, and the mean quadratic slope, respectively, and β_{01}, β_{11}, and β_{21} are the variance for growth parameters, respectively. ζ_{0i}, ζ_{1i}, and ζ_{2i} are their error terms. Unconditional models such as linear (Model 0) and quadratic (Model I) were fitted to the data to examine the shape of growth trajectories (see Figures 2a and b).

The conditional model (see Figure 2c) was fitted to the data to explain the variation among participants in growth factors (Byrne et al., 2008). The measurement model with sleep quality (SQ) as a time-varying covariate is in Equation 3:

$$y_{it} = (\eta_{0i} + \eta_{1i}a_t) + (\gamma_t * SQ_{it}) + \varepsilon_{it} \quad (3)$$

where γ_t is the coefficient of the covariate effects on growth factors; in this case, y_{it} is the sum of the errors and the covariate effect. Sleep quality (Model II), resilience (Model III), and stress (Model IV) were added to the conditional model as time-varying covariates, respectively.



Note. i - intercept, s - slope, q - quadratic slope, c - categorical latent class, WB - subjective well-being, SQ – sleep quality

Figure. 2. Path diagrams for four types of Growth Modeling

The unconditional and conditional LGCMs were fitted to the data using M*plus* 7 (L. Muthén & Muthén, 1998-2012). All models were estimated using the maximum likelihood (ML) estimation. The comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) were considered to evaluate the model-data fit. The recommended cutoffs of CFI>0.95, RMSEA<0.05, and SRMR<0.05 as indicating a good model fit and CFI>0.90, RMSEA<0.08, and SRMR<0.08 as indicating an acceptable model fit were used (Brown, 2015; Hu & Bentler, 1999). The log-likelihood difference test (T_D) was utilized to compare nested models (B. Muthén & Muthén, 2020).

Latent Class Growth Analysis

Figure 2d demonstrates an unconditional LCGA model. The measurement model part is like an unconditional LGCM,

$$y_{it}|(C_i = c) = \eta_{0i} + \eta_{1i}a_t + \varepsilon_{it} \quad (4)$$

where y_{it} is the observed score of participant i at time point t. y_{it} is conditional on the class membership C_i. a_t is the time score, η_{0i} and η_{1i} are the intercept and slope, and ε_{it} is the error score for participant i in class c. The structural models are like unconditional LGCM, but it includes the categorical latent class variable c, which apprehends the heterogeneity in the population (Nylund et al., 2007). The structural model part as

$$\eta_{0i} = \beta_{c00} + \zeta_{c0i}$$
$$\eta_{1i} = \beta_{c10} + \zeta_{c1i} \quad (5)$$

where β_{c00} is the mean intercept and β_{c10} is the mean slope within class *c*. ζ_{c0i} and ζ_{c1i} are error scores for participant *i* in class *c*. In LCGA, all individual latent trajectories within classes are assumed to be homogeneous and permitted to vary only among classes (Nagin, 1999). The LCGA model was evaluated by a sequentially increasing number of latent classes (one-, two-, and three-class) to determine the class formation. The ML approach was employed to estimate the model.

One of the most challenging LCGA tasks is properly characterizing the latent class number. Suppose the researcher has no prior information about the latent class number in the data. In that case, the most frequent method is to analyze models with different class numbers and compare model-fit indices (Tofighi & Enders, 2007). Firstly, it is recommended to carefully check the estimation output, looking for outlier parameter estimates and other problems (Ram & Grimm, 2009). Secondly, models can be evaluated by comparing *information criteria indices* such as Akaike Information Criterion (AIC) (Akaike, 1987), Bayesian Information Criterion (BIC) (Schwarz, 1978), and Sample Size Adjusted BIC information criteria (SSA-BIC) (Sclove, 1987). Lower values indicate better-fitting models. Thirdly, nested models can be compared according to likelihood ratio tests (LRTs) that compare models with *c* and *c-1* latent classes. The LRTs are the adjusted Lo-Mendell-Rubin LRT (LMR-LRT), Vuong-Lo-Mendell-Rubin LRT (VLMR-LRT) (Lo et al., 2001), and the parametric Bootstrap LRT (BLRT) (McLachlan & Peel, 2000). A significance test ($p < 0.05$) of the VLMR-LRT or LMR-LRT points out that the model with the *c–1* class should be rejected in favor of the model with the *c* classes (Nylund et al., 2007). Finally, models can be evaluated concerning the accuracy with which individuals have been appointed as belonging to one group. Entropy indicates the degree of classification uncertainty. It ranges from 0.00 to 1.00, high values (>0.80) suggest that individuals are classified as reliable and that there is sufficient separation among classes (Collins & Lanza, 2010). Average posterior probability (APP) values are generated by averaging the class probabilities of individuals with the highest posterior probability. When the APP value exceeds 0.70, individuals in a latent class have similar growth patterns (Nagin, 1999).

Results

Results of Research Question I

Unconditional LGCMs such as Model 0 (linear) and Model I (quadratic) were specified to predict the mean and the variance of growth factors across individuals. Table 3 summarizes unconditional model fit indices. The model-data fit indices indicate an inadequate fit of Model 0 to the data ($\chi^2 = 17.87(5), p > 0.05$; CFI = 0.86, TLI = 0.84, SRMR = 0.06 and RMSEA = 0.13). The model-data fit indices indicate an adequate fit of Model I (CFI = 1.00, TLI = 1.00, SRMR = 0.005, and RMSEA = 0.00). Because of the fully saturated model, model fit indices always provide a perfect fit to the data. According to nested model comparisons, the log-likelihood difference test revealed a non-significant difference between these two unconditional models ($T_D = 17.21(4), p >$ 0.01). However, because Model 0 is more parsimonious than Model I, it was determined to be the best-fitting model, and it was concluded that students showed a linear growth pattern in subjective well-being.

Table 3. Model fit indices for unconditional LGCMs

	$\chi^2(df)$	AIC	BIC	RMSEA	SRMR	CFI	TLI	T_D
Model 0	17.87 (5)	3300.94	3328.28	0.13	0.06	0.86	0.84	-
Model I	0.79 (1)	3291.15	3330.63	0.00	0.005	1.00	1.00	17.21 (4)

The mean intercept and slope estimates were 11.49 and -0.21, respectively ($p < 0.05$). The average subjective well-being at the initial time was approximately 11.49, and the weekly decrease in values was approximately -0.21 points on average. The estimate of variance intercept was 6.74, indicating inter-individual differences in the initial time point ($p < 0.05$). The estimate of variance slope was 0.81, indicating inter-individual differences in growth rate ($p < 0.05$).

Results of Research Question II

Sleep quality (Model II), resilience (Model III), and stress (Model IV) variables as time-varying covariates were cumulatively added to the unconditional linear growth model. In conditional LGCMs, the slope growth factor is defined as a function of the intercept factor, controlling for covariates. Table 4 summarizes model fit indices.

Table 4. Model fit indices for conditional LGCMs

	$\chi^2(df)$	AIC	BIC	RMSEA	SRMR	CFI	TLI	T_D
Model 0	17.87 (5)	3300.94	3328.28	0.13	0.06	0.86	0.84	-
Model II	42.41 (17)	3221.04	3260.44	0.10	0.06	0.87	0.84	78.34(4)*
Model III	45.32 (29)	2999.89	3051.41	0.06	0.04	0.96	0.94	139.30(4)*
Model IV	43.64 (41)	2833.77	2897.41	0.03	0.03	0.98	0.98	177.60(4)*

* $p < 0.05$

Considering conditional LGCMs fit indices, Model IV fitted the data better than the previous ones after controlling time-varying covariates' effects (sleep quality, resilience, and stress). The log-likelihood difference test for nested models revealed significant differences between these conditional models ($p < 0.05$). This means that adding to covariates improved step-by-step model fits. In Model IV, the CFI and TLI were reported to be 0.98 better in magnitude than in Model 0. The RMSEA and SRMR were enhanced to an acceptable level of 0.03. Model IV had the lowest AIC and BIC values, indicating a better model-data fit. The observed mean value, unconditional (Model 0), and conditional (Model IV) mean estimate values were plotted in Figure 3. Model IV appeared to be the model that best captured the change in the data.

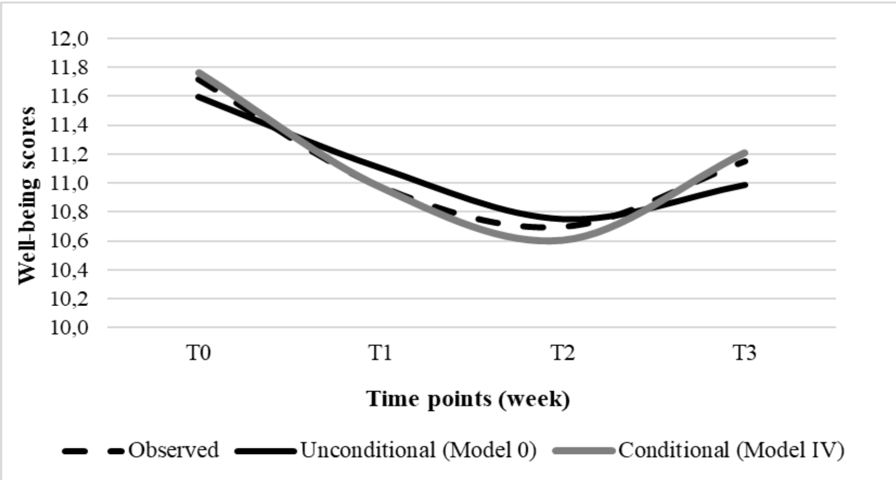


Figure. 3. The plot of observed mean value, unconditional and conditional LGCMs mean estimates

Table 5 summarizes conditional model estimates. The rate of change decreased, and this decrease occurred faster (slope values for Model 0 and Model IV were -0.21 and -1.22, respectively). The growth parameters' standard error estimates were reduced compared to the unconditional model. The conditional model results showed that covariates significantly affected subjective well-being scores at every time point ($p < 0.05$). The mean intercept and mean slope estimates were 13.2 and -1.22, respectively, controlling for covariates. The intercept and slope variance became 2.66 and 0.36, respectively, in contrast to 6.74 and 0.81, in the unconditional model. There is a decline of 60% in intercept variance and 55% in slope variance explained by the covariates.

Table 5. Parameter estimations from the unconditional and conditional LGCMs

Parameters	Estimate	Estimate/SE
Unconditional Model (Model 0)		
Mean intercept (β_{00})	11.5*	41.27
Variance of intercept (β_{01})	6.74*	4.16
Mean slope (β_{10})	-0.20*	-1.96
Variance of slope (β_{11})	0.81*	2.62
Conditional Model (Model IV)		
Mean intercept (β_{00})	13.2*	15.84
Variance of intercept (β_{01})	2.66*	3.78
Mean slope (β_{10})	-1.22*	-2.85
Variance of slope (β_{11})	0.36*	2.30

* $p < 0.05$

Results of Research Question III

The LCGA model fit by consecutively increasing the number of latent classes (from one to three) was evaluated to determine the latent growth trajectory classes. The results increasingly presented better (i.e., smaller) AICs, BICs, and SSA-BICs (Table 6).

Table 6. Model fit criteria for class formation for LCGA

Model-Fit Indexes	LC1	LC2	LC3
AIC	3388.22	3327.56	3310.24
BIC	3406.45	3354.89	3346.69
SSA-BIC	3387.45	3326.40	3308.71
Entropy	-	0.76	0.79
LMR-LRT *p*	-	0.05*	0.07
VLMR *p*	-	0.05*	0.06
BLRT *p*	-	0.00*	0.00*

*$p < 0.05$; LC = latent class

Table 6 shows that comparing the current model against the model with one less class than the current model of choice should give an LMR-LRT *p*-value that is significant ($p < 0.05$). The LMR-LRT indicated that the data fit with the two-class model was not improved with the three-class model. The BLRT showed a statistically significant difference between the two-class versus the three-class models. The VLMR showed a non-significant difference between the two-class versus three-class models. The number of latent classes is subject to the model fit indices, the research question, parsimony, and interpretability. Hence, the two-class model was determined to be the best-fit model.

An entropy value summarizes individual class probabilities to evaluate classification quality. The entropy value of 0.76 showed good quality in classifying students into the two classes. The APP values were all reasonably high (0.85 or higher), near 1.0. Together, latent class findings recommend a good model fit for the two-class model. The estimated means of each class based on posterior probabilities are presented in Figure 4. This plot indicates that the sample shows heterogeneous growth in subjective well-being and that the amount of change does not occur similarly for the entire sample.

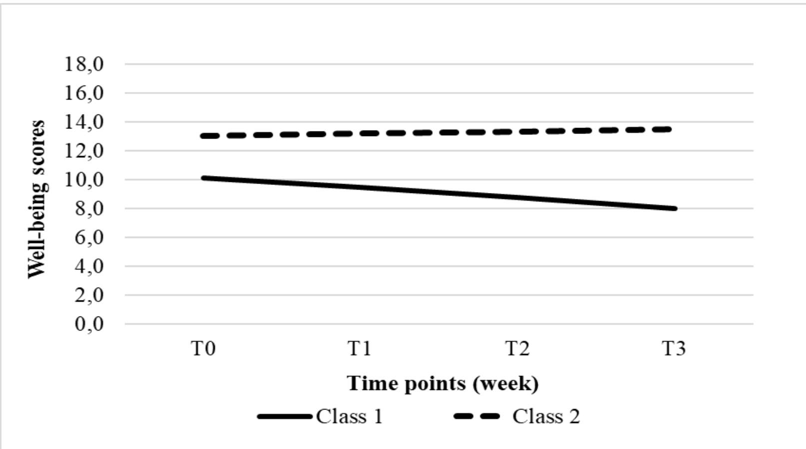


Figure 4. Estimated means of latent classes.

According to the growth patterns, Class 1 (55%) was the largest class. Class 1 members began with an average score of 10.13 at the initial time point and decreased by -0.81 points over time ($p < 0.05$). Members of Class 2 (45%) began with an average 13.03 score at the initial time point and increased by 0.16 points over time ($p < 0.05$). While the unconditional LGCM indicated a decreasing trend over time, this decline appeared limited to Class 1. This result suggests the existence of unobserved heterogeneity in the sample.

Discussion

The present study examined the latent growth trajectories of subjective well-being over time using a person-centered longitudinal measurement method. In the first stage, the unconditional LGCM demonstrated that the average growth trajectory was a linear decline over time with inter-individual differences at the initial time point. It is in line with previous studies that supported the linear growth of subjective well-being (Diener et al., 2018). In the second stage, adding the covariates to the unconditional model improved the model-data fit, and growth trajectories were much steeper than in the unconditional model. The results supported the hypothesis that changes in covariates influence changes in subjective well-being. It has been empirically supported that the contribution of the longitudinal measurement methods in concurrently modeling the time-varying covariates and observed variables (Wickrama et al., 1997).

It is quite possible that differentiation of latent trajectories exists within the larger population in educational research (Jung & Wickrama, 2008). The sources of this heterogeneity can be groups as observed or unobserved groups. In the third stage, the presence of unobserved distinct growth trajectories was explored with the LCGA model. Based on parsimony and interpretability, the two-class model was chosen as the best model to explain the heterogeneity of growth trajectories. One of the latent trajectory classes (Class 1) displayed similar growth trajectories with the unconditional model, but the slope was much smoother. The second latent trajectory class (Class 2), unlike Class 1, displayed an increasing trend over time. The results demonstrated that subjective well-being changed over time, and the rate of this change, as well as its covariates, were not constant for the entire sample. Consistent with previous studies, the results revealed that subjective well-being had a dynamic structure and supported the importance of using longitudinal measurement methods to explore the change process (Fernandez-Rio et al., 2021). The results highlighted the need to examine the growth process longitudinally rather than cross-sectionally and identify unobserved heterogeneity within the population (Muthén & Brown, 2009).

The correspondence between construct and measurement design must be required for making proper and valid inferences from the data (Cronbach & Meehl, 1955). Longitudinal studies can support us in understanding transitions in people's lives, interruptions, trauma, and turning points that might contribute to comprehension (Goswami et al., 2016). In this regard, longitudinal data are necessary for constructs that are open to change by nature, such as depression (Barboza, 2020), mental development (Lee, 2020), and language development (Elahi-Shirvan et al., 2021) to analyze and understand the growth over time and answer questions about how they relate to other important competencies. The Latent Transition Model (Collins & Wugalter, 1992) and Latent State-Trait Models (Cole, 2012) can also be used to model longitudinal growth patterns.

Conclusion

The current study utilized a person-centered longitudinal measurement model to examine subjective well-being growth trajectories. The results revealed that subjective well-being showed inter-individual and intra-individual variation over time, and the rate of these changes, as well as its covariates, differed among individuals. Longitudinal research has revealed several statistical methodologies in which the origins of intra-individual and inter-individual variation must be considered jointly. The longitudinal statistical approaches employed in this study differ from others in two ways: they combine mean and covariance structures and allow measurement error to be evaluated and modeled simultaneously (Byrne et al., 2008). By controlling for the effect of diverse sources of variability on subjective well-being, inter-individual differences in latent growth patterns and intra-individual change were explored in detail. The categorical latent class variable was used to model the sample heterogeneity in the latent class growth analysis. Several research studies have stressed the importance of considering the heterogeneity within the sample while studying inter-individual variation in a longitudinal pattern (Wang & Bodner, 2007). Even a small percentage of a group with distinct features in the sample can suppress the variation pattern for the entire sample and obscure alternate development curves (Muthén, 2002). Ignoring the characteristics of latent classes with various developmental patterns can hide the dynamic interactions that lead to significant outcomes (Connell & Frye, 2006). The results highlighted the importance of examining continuous and cumulative processes longitudinally and evaluating latent classes based on the possibility of a heterogeneous distribution within the sample (Muthén & Brown, 2009).

Limitations

The current study includes several limitations due to its illustrative nature. Firstly, the sample consisted of student volunteers, with missing data excluded from the study. This restriction was performed to keep the study simple and parsimonious. It is stressed that a larger sample size is required in longitudinal studies to more precisely model estimations (Diallo et al., 2017); however, in recent years, robust estimation methods have been established for proper model estimations with small sample sizes (Shi et al., 2021). A cross-validation study is recommended with different sample sizes and the inclusion of students with missing data. Additionally, the majority of the sample consisted of female students, mainly due to their voluntary participation. Therefore, it is recommended to include a more diverse group to obtain more accurate estimation results. Secondly, four weekly repeated measures were used to model growth trajectories. It can be investigated how different time intervals, such as daily or weekly, affect intra- and inter-individual changes. Thirdly, subjective well-being was operationalized using observed indicators such as happiness, peace, satisfaction, and energy. Moreover, a limited number of available covariates were used to predict the model. The effects of different covariates can be tested to define the growth process properly. The effect size of the covariates can be investigated in future studies using various methods (Feingold, 2021; Li & Harring, 2017). Finally, since the later measures have progressively lower correlations with the earlier measures as a function of increasing time, the effects of covariates were modeled with indicators concurrently. The Autoregressive Latent Trajectory Model (Bollen & Curran, 2004; Scott, 2021) can also be used to define the growth trajectories in longitudinal data. This model has one thing in common with the autoregressive model; the ability to include knowledge of the past values of a variable to estimate current values, which allows us to model growth trajectories with lagged influences (cross-lagged = 1, 2,..).

Recommendations

In this study, LCGA approaches were used to define latent trajectory classes. These models assume that no inter-individual differences are fixed to zero, meaning all individuals in a given latent class are similar. GMM can be used to explore latent classes if the variance of growth factors is statistically significant, and the sample size is sufficient for within-class variance estimation. External variables (covariates or distal outcomes) can be added in various ways to the model (Bakk & Kuha, 2020). The present study did not investigate the effect of covariates on latent class formation. Covariate variables can be utilized to explain the class membership and the class assignment information can be used as a predictor for the distal outcome for further analyses. It is suggested that longitudinal measurement methods be utilized for more reliable and valid inferences from measurements in educational and psychological sciences, where individual development is more essential (Fukkink & van Verseveld, 2020).

Author (s) Contribution Rate

First author: Conceptualization, design, data acquisition, data analysis and interpretation, writing, drafting manuscript.
Second author: Editing and reviewing, supervision, critical revision of the manuscript, final approval.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval

Ethical permission (2018/75228) was obtained from Gazi University Ethical Committee institution for this research.

References

Aili, K., Campbell, P., Michaleff, Z. A., Strauss, V. Y., Jordan, K. P., Bremander, A., Croft, P., Bergman, S. (2021). Long-term trajectories of chronic musculoskeletal pain: a 21-year prospective cohort latent class analysis. *Pain, 162*, 1511-1520. https://doi.org/10.1097/j.pain.0000000000002137

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52*, 317-332. https://doi.org/10.1007/BF02294359

Aşkar, P., & Yurdugül, H. (2009). The using of Latent Growth Models for educational researches. *Elementary Education Online, 8*(2), 534-555. http://www.ilkogretim-online.org/fulltext/218-1596681446.pdf?1621152578

Bakk, Z., & Kuha, J. (2020). Relating latent class membership to external variables: An overview. *British Journal of Mathematical and Statistical Psychology, 74*, 340-362. https://doi.org/10.1111/bmsp.12227

Barboza, G. E. (2020). Child maltreatment, delinquent behavior, and school factors as predictors of depressive symptoms from adolescence to adulthood: a Growth Mixture Model. *Youth & Society, 52*(1), 27-54. https://doi.org/10.1177/0044118X17721803

Berlin, K., Parra, G., & Williams, N. (2014). An introduction to Latent Variable Mixture Modeling (part 2): longitudinal Latent Class Growth Analysis and Growth Mixture Models. *Journal of Pediatric Psychology, 39*(2), 188-203. https://doi.org/10.1093/jpepsy/jst085

Bilir, M. K., Binici, S., & Kamata, A. (2008). Growth Mixture Modeling: application to reading achievement data from a large-scale assessment. *Measurement and Evaluation in Counseling and Development, 41*(2), 104-119. https://doi.org/10.1080/07481756.2008.11909825

Bollen, K. A., & Curran, P. J. (2004). Autoregressive Latent Trajectory (ALT) models: a synthesis of two traditions. *Sociological Methods & Research, 32*(3), 336-383. https://doi.org/10.1177/0049124103260222

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford.

Byrne, B. M., Lam, W. W., & Fielding, R. (2008). Measuring patterns of change in personality assessments: an annotated application of Latent Growth Curve Modeling. *Journal of Personality Assessment, 90*(6), 536-546. https://doi.org/10.1080/00223890802388350

Cole, D. A. (2012). Latent trait-state models. In R. H. (Ed.), *Handbook of structural equation modeling* (s. 585-600). Guilford.

Collins, L. M. (2006). Analysis of longitudinal data: The integration of theoretical model, temporal design and statistical model. *Annual Review of Psychology, 57*, 505-528. https://doi.org/10.1146/annurev.psych.57.102904.190146

Collins, L. M., & Lanza, S. T. (2010). *Latent Class and Latent Transition Analysis: with applications in the social, behavioral, and health sciences*. John Wiley & Sons.

Collins, L. M., & Wugalter, S. E. (1992). Latent class models for stage-sequential dynamic latent variables. *Multivariate Behavioral Research, 27*(1), 131-157. https://doi.org/10.1207/s15327906mbr2701_8

Connell, A. M., & Frye, A. A. (2006). Growth Mixture Modelling in developmental psychology: overview and demonstration of heterogeneity in developmental trajectories of adolescent antisocial behaviour. *Infant and Child Development, 15*(6), 609-621. https://doi.org/10.1002/icd.481

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52*(4), 281-302. https://doi.org/10.1037/h0040957

Curran, P. J., & Willoughby, M. T. (2003). Implications of latent trajectory models for the study of developmental psychopathology. *Development and Psychopathology, 15*(3), 581-612. https://doi.org/10.1017/S0954579403000300

Curran, P. J., & Wirth, R. J. (2004). Interindividual differences in intraindividual variation: balancing internal and external validity. *Measurement (Mahwah N J), 2*(4), 219-247. https://doi.org/10.1207/s15366359mea0204_2

Diallo, T. M., Morin, A. J., & Lu, H. Z. (2017). The impact of total and partial inclusion or exclusion of active and inactive time invariant covariates in Growth Mixture Models. *Psychological Methods, 22*(1), 166-190. https://doi.org/10.1037/met0000084.

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour, 2*, 253-260. https://doi.org/10.1038/s41562-018-0307-6

Duncan, T. E., & Duncan, S. C. (2009). The ABC's of LGM: an introductory guide to Latent Variable Growth Curve Modeling. *Social Personality Psychology Compass, 3*(6), 979-991. https://doi.org/10.1111/j.1751-9004.2009.00224.x

Elahi Shirvan, M., Taherian, T., Shahnama, M., & Yazdanmehr, E. (2021). A longitudinal study of foreign language enjoyment and L2 grit: a Latent Growth Curve Modeling. *Front. Psychol., 12*. https://doi.org/10.3389/fpsyg.2021.720326

Feingold, A. (2021). Effect of parameterization on statistical power and effect size estimation in Latent Growth Modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 28*(4), 609-621. https://doi.org/10.1080/10705511.2021.1878895

Fernandez-Rio, J., Cecchini, J. A., Mendez-Gimenez, A., & Carriedo, A. (2021). Mental well-being profiles and physical activity in times of social isolation by the COVID-19: a latent class analysis. *International Journal of Sport and Exercise Psychology*. https://doi.org/10.1080/1612197X.2021.1877328

Fukkink, R. G., & van Verseveld, M. (2020). Inclusive early childhood education and and care: a longitudinal study into the growth of interprofessional collaboration. *Journal of Interprofessional Care, 34*(3), 362-372. https://doi.org/10.1080/13561820.2019.1650731

Goswami, H., Fox, C., & Pollock, G. (2016). The current evidence base and future needs in ımproving children's well-being across Europe: is there a case for a comparative longitudinal survey? *Child Indicators Research, 9*, 371-388. https://doi.org/10.1007/s12187-015-9323-5

Gottfried, A. E., Nylund-Gibson, K., Gottfried, A. W., Morovati, D., & Gonzalez, A. M. (2016). Trajectories from academic intrinsic motivation to need for cognition and educational attainment. *The Journal of Educational Research, 110*(6), 642-652. https://doi.org/10.1080/00220671.2016.1171199

Hertzog, C., & Nesselroade, J. R. (2003). Assessing psychological change in adulthood: an overview of methodological issues. *Psychology and Aging, 18*(4), 639-657. https://doi.org/10.1037/0882-7974.18.4.639

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. https://doi.org/10.1080/10705519909540118

Jung, T., & Wickrama, K. A. (2008). An introduction to Latent Class Growth Analysis and Growth Mixture Modeling. *Social and Personality Psychology Compass, 2*(1), 302-317. https://doi.org/10.1111/j.1751-9004.2007.00054.x

Kane, M. T. (2013). Validating the interpretations and uses of test scores. *Journal of Educational Measurement, 50*(1), 1-73. https://doi.org/10.1111/jedm.12000

Kim, Y., Kang, M., Tacon, A., & Morrow, J. (2016). Longitudinal trajectories of physical activity in women using Latent Class Growth Analysis: the WIN study. *Journal of Sport and Health Science, 5*(4), 410-416. https://doi.org/10.1016/j.jshs.2015.04.007

Lee, J. (2020). Trajectories of mental health across baby boomers: Latent Growth Curve Modeling for depression. *Social Work in Mental Health, 18*(1), 96-120. https://doi.org/10.1080/15332985.2019.1683674

Li, M., & Harring, J. R. (2017). Investigating approaches to estimating covariate effects in Growth Mixture Modeling: A simulation study. *Educational and Psychological Measurement, 77*(5), 766-791. https://doi.org/10.1177/0013164416653789

Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika, 88*(3), 767-778. https://doi.org/10.1093/biomet/88.3.767

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

McLachlan, G., & Peel, D. (2000). *Finite mixture modeling.* Wiley.

Menard, S. (2008). *Handbook of longitudinal research: Design, measurement, and analysis.* Academic.

Meredith, W., & Tisak, J. (1990). Latent curve analysis. *Psychometrika, 55*(1), 107-122. https://doi.org/10.1007/BF02294746

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

Muthén, B. O. (2002). Beyond SEM: General Latent Variable Modeling. *Behaviormetrika, 29*(1), 81-117. https://doi.org/10.2333/bhmk.29.81

Muthén, B. O., & Muthén, L. K. (2020, March). *Chi-square difference testing using the Satorra–Bentler scaled chi-square.* http://www.statmodel.com/chidiff.shtml

Muthén, B., & Brown, H. C. (2009). Estimating drug effects in the presence of placebo response: causal inference using Growth Mixture Modeling. *Statistics in Medicine, 28*(27), 3363-3385. https://doi.org/10.1002/sim.3721

Muthén, B., & Shedden, K. (1999). Finite Mixture Modeling with mixture outcomes using the EM algorithm. *Biometrics, 55*(2), 463-469. https://doi.org/10.1111/j.0006-341x.1999.00463.x

Muthén, L. K., & Muthén, B. O. (1998-2012). *Mplus user's guide (7th Edition).* Muthén & Muthén.

Nagin, D. (1999). Analyzing developmental trajectories: a semi-parametric, group-based approach. *Psychological Methods, 4*(2), 139-157. https://doi.org/10.1037/1082-989X.4.2.139

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in Latent Class Analysis and Growth Mixture Modeling: a Monte Carlo Simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535-569. https://doi.org/10.1080/10705510701575396

Pierce, M., Mcmanus, S., Hope, H., Hotopf, M., Ford, T., Hatch, S. L., . . . Abel, K. M. (2021). Mental health responses to the COVID-19 pandemic: a latent class trajectory analysis using longitudinal UK data. *Lancet Psychiatry, 8*, 610-619. https://doi.org/10.1016/S2215-0366(21)00151-6

Ployhart, R. E., & Vanderberg, R. J. (2010). Longitudinal research: the theory, design, and analysis of change. *Journal of Management, 36*(1), 94-120. https://doi.org/10.1177/0149206309352110

Ram, N., & Grimm, K. J. (2009). Growth Mixture Modeling: a method for identifying differences in longitudinal change among unobserved groups. *International Journal of Behavioral Development, 33*(6), 565-576. https://doi.org/10.1177/0165025409343765

Ruscio, J., & Ruscio, A. M. (2008). Categories and dimensions: advancing psychological science through the study of latent structure. *Current Directions in Psychological Science, 17*(3). https://doi.org/10.1111/j.1467-8721.2008.00575.x

Schwarz, G. (1978). Estimating the dimension of a model. *The Annuals of Statistics*, *6*(2), 461-464. https://doi.org/10.1214/aos/1176344136

Sclove, L. S. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, *52*, 333-343. https://doi.org/10.1007/BF02294360

Scott, P. W. (2021). Accounting for Time-Varying Inter-Individual Differences in Trajectories when Assessing Cross-Lagged Models. *Structural Equation Modeling: A Multidisciplinary Journal*, *28*(3), 365-375. https://doi.org/10.1080/10705511.2020.1819815

Shi, S., DiStefano, C., Zheng, X., Liu, R., & Jiang, Z. (2021). Fitting latent growth models with small sample sizes and non-normal missing data. *International Journal of Behavioral Development*, *45*(2), 179-192. https://doi.org/10.1177/0165025420979365

Tofighi, D., & Enders, C. (2007). Identifying the correct number of classes in a Growth Mixture Model. In G. R. Hancock, *Mixture models in latent variable research* (s. 317-341). Information Age.

Wang, M., & Bodner, T. E. (2007). Growth Mixture Modeling: identifying and predicting unobserved subpopulations with longitudinal data. *Organizational Research Methods*, *10*(4), 635-656. https://doi.org/10.1177/1094428106289397

Wickrama, K. A., Lorenz, F. O., & Conger, R. D. (1997). Parental support and adolescent physical health status: a Latent Growth-Curve Analysis. *Journal of Health and Social Behavior*, *38*(2), 149-163. https://doi.org/10.2307/2955422

Willett, J., & Sayer, A. (1994). Using covariance structure analysis to detect correlates and predictors of individual change over time. *Psychological Bulletin*, *116*(2), 363-381. https://doi.org/10.1037/0033-2909.116.2.363