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Research Paper

Measuring academic resilience of socioeconomically disadvantaged students in Taiwan 2011-2017: Two-part latent class growth modeling based on IRT scores

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Abstract. Academic resilience is a critical topic that has been around for decades and contains a variety of theoretical models and research approaches. In this current study, we adopted the developmental view of resilience. We combined the person-focused (classification and trajectory) and variable-focused (regression) methods to analyze the longitudinal data of 744 students from the TDCYP 2011-2017. We conducted item response theory (IRT) models and a latent class growth modeling framework. First, we measured each person's latent trait level by IRT and simultaneously identified the classes by positive outcome (academic self-concept) and risk factors. Eventually, to explain the class membership and growth factors by adding covariates. The finding of this study as follows, (1) the four-class model was selected, and they are the competent group (17%), the resilient group (34%), the vulnerable group (31%), and the maladaptive group (18%). (2) The developmental hypothesis of academic resilience was not confirmed because the slope factors of academic self-concept and two groups of risk factors showed no significance. (3) Moreover, we found gender, mental health (illness), and teacher support play critical roles in this study, and they could explain the growth trends and even the membership classifying. The family support and poverty factors were lack of influence might due to the data properties. Importantly, this study can advise educators that it is worth further studying and practicing that school-based context on how to support a student, especially the socioeconomically disadvantaged.

Keywords: Academic resilience, socioeconomically disadvantaged, latent class growth modeling, longitudinal IRT, Taiwan Database of Children and Youth in Poverty (TDCYP).

INTRODUCTION

Academic resilience is a critical topic for international educational research, such as PISA (Agasisti *et al*., 2018), and it is also a topic that has been around for decades and contains a variety of theoretical models (Martin and Marsh, 2008; Masten *et al*., 1999) and research approaches (Masten, 2001; Tudor and Spray, 2017). Several approaches can deal with longitudinal data about academic resilience, such as classification modeling. In this approach, resilient trajectories are an essential person-focused approach. Even researchers with a trait perspective of academic resilience still value longitudinal data analysis (Liew *et al.*, 2018; Martin *et al.*, 2010; Murphy *et al*., 2014). Otherwise, the *developmental cascades* (Masten *et al.*, 2005) or Mathew effect (the better getting better and the worse conveying worse) is a popular theory in developmental psychology, as long as the issue of cumulative advantage (or disadvantage) is involved. Masten *et al.* (2005) used this concept to explore the 20-year long-term relationship between academic achievement and external and internal problems.

In this current study, we measured the developmental process in the development model of resilience (Masten, 2001, 2014; Masten *et al.*, 1999), as well as investigated the associations within related variables through a two-part latent growth mixture modeling framework (Muthén, 2006; Muthén and Muthén, 2000) and item response models (Cai, 2010; Muraki, 1992), respectively.

Academic resilience as a trait or process

Over the past decades, opinions on academic resilience have been based on trait and development perspectives. Researchers who recognize academic resilience as a trait have worked to develop measurement tools such as Cassidy's (2016) Academic Resilience Scale (ARS-30) and to construct theories such as classical resilience and everyday resilience, as proposed by Martin (2013).

According to Martin (2013), there is a slight difference between *classical resilience* and *everyday resilience*. Classical resilience is associated with chronic issues, such as depression, anxiety, dropping out of school, rebellion against teachers, etc., and the adversities are often more severe, such as chronic underachievement or poverty in the family (Martin and Marsh, 2008; Tudor and Spray, 2017). In contrast, most students in school may not face serious life challenges but more everyday academic problems, such as facing the pressure of reporting deadlines. Thus, everyday academic resilience is often related to negative self-confidence, motivation, engagement, peer interaction, and teacher-student interaction (Martin and Marsh, 2008; Tudor and Spray, 2017).

However, the researchers of developmental psychology (Masten, 2001) have argued that considered resilience as a trait ignored the process by an individual to adapt to adversity and the interactions among different systems. Broadly, resilience is described as a system's capacity to adjust successfully to struggles that adversely impact the system's function, survival, or future development (Masten, 2001; Masten, 2014).

In this current study, academic resilience is defined as the adjustment outcomes that positively disadvantaged individuals who struggled with adversity. That is, we simultaneously measured the adaptation and adversity levels, then identified the latent structure of the different developmental patterns of the students.

Measuring academic resilience

Person-focused approach

The research approach to resilience can be divided into variable-focused and person-focused; the two methods have pros and cons. For person-focused approaches, Masten (2001) introduced a full classification model (expanded classic model), including the students in both high and low adversity exposure. The four major groups are (1) the **competent group** with good adjustment and low adversity, (2) the **resilient group** with good adjustment but high adversity, (3) the **vulnerable group** with poor adjustment but low adversity, and (4) the **maladaptive group** with poor adjustment and high adversity.

Variable-focused approach

The multiple regression model is usually applied for variable-focused approaches (risk factors as the explanatory variables and adaptive outcomes as the response variable). The promoters (or protective factors) can be added to the model, then the mediating and moderating effects can be tested to understand the resilience mechanism between these variables.

According to Tudor and Spray (2017), there are over ten tools for measuring academic resilience. The most important of them which contain risk and protection factors are the Resilience and Youth Development Module (RYDM) (Jowkar *et al.*, 2011) and the Academic Risk and Resilience Scale (ARRS) (Martin, 2013). The former (RYDM) uses low socioeconomic status as risk factors, school factors and family factors (e.g., caring, high expectations, meaningful engagement), and intrinsic factors (e.g., cooperation, self-efficacy, empathy, problem-solving, self-awareness) as protective factors. The latter (ARRS) uses ten items on academic adversity as risk factors, including repetition, failure, suspension, withdrawal, learning disabilities, etc. Each item needs to be responded to as yes or no. If one of the ten risk items was answered yes, the other four items on academic resilience must be answered.

Tudor and Spray's (2017) study also extends Masten *et al.* (1999) definition of resilience into two dimensions: (1) risk/adversity and (2) adaptive behavior. Risk factors or adversity usually focus on low socioeconomic status (SES) or ethnic minorities. Positively adaptive outcomes imply accomplishing developmental tasks (Masten, 2014). Tudor and Spray (2017) suggests that developmental tasks refer to academic performance in adversity in the framework of academic resilience. According to traditional research on resilience, the protective factors for individuals against adversity include self-esteem, self-efficacy, autonomy, engagement in school, and value in school. The environmental protective factors include parent involvement, social ties at school, and the classroom environment.

To date, positive psychology has progressed through at least two waves. The first wave (PP 1.0, Pawelski, 2016a, 2016b) focused on positive emotions, traits, behaviors, cognition, etc., such as well-being, flourishing, and mindfulness. The second wave (PP 2.0, Wong, 2011) simultaneously considered polarity - positive and negative concepts. This trend of PP 2.0 support measuring the bipolar concept (positive academic self-concept and risk factors) in this current study.

Related and protective factors

Most studies considered academic resilience a multidimensional construct that implied academic resilience might involve several personal latent resources. Cassidy's (2016) ARS-30 scale contains three factors: (1) perseverance, (2) reflecting and adaptive help-seeking, as well as (3) negative affect and emotional response. In addition, Martin and Marsh (2006) and Martin *et al.* (2010) proposed the 5Cs model of classical academic resilience: confidence (e.g., self-efficacy), coordination (e.g., planning), control (e.g., low self-esteem), composure (e.g., low anxiety) and commitment (e.g., perseverance), with a high negative correlation between anxiety and academic resilience.

According to Duncan and Brooks-Gunn (2000), the effects of poverty on children and adolescents come from low-income family environments, quality of care, financial stress, parental mental health status, parent-child relationships, plce of residence, and community relationships. Economically disadvantaged children are handicapped by adversity in their initial state.

Take the Skills for Life (SFL) Programme as an example (Murphy *et al*., 2014). Mental health status in grade 1 and grade 3 can predict later academic achievement. In contrast, children whose mental health improved between grades 1 and 3 were more advanced academically than those whose mental health did not improve or become worse. Specifically, Masten and Barnes (2018) listed the core questions in resilience studies; for risks, such as trauma, neglect, poverty, and war, etc.; for adaptation, such as mental health, happiness, and work achievement; and for protective factors, such as familial and relational, community, etc. Fullerton *et al.* (2021) found the integrated resilience resources can predict mental well-being and adjustment. Liew *et al.* (2018) provided a longitudinal analysis but showed no mediator effect of teacher-student relationships between resilience and academic achievement.

Research questions

In the past decades, there have been undertaken many studies on academic resilience (Agasisti *et al.*, 2018; Cassidy, 2016; deRoon-Cassini *et al.*, 2010; Jowkar *et al.*, 2011; Liew *et al.*, 2018; Martin, 2013; Martin and Marsh, 2006, 2008; Rudd *et al.*, 2021; Tudor and Spray, 2017). This current study focused on a measuring approach and implementation using the latent growth mixture modeling framework, combining person-focused and variable-focused approaches (Muthén and Muthén, 2000) and dealing with longitudinal data. The latent class or mixture model can be applied to examine the Masten model of resilience and the growth model, which illustrates the resilient trajectories in a person-focused way. Moreover, variable-focused issues can be conducted by adding covariates into a mixture model as explanatory variables.

In addition to academic self-concept and risk factors (both for describing academic resilience), we also considered gender, poverty, mental health (illness), as well as caring adults and a supportive environment (family and school) which will be adopted in explaining academic resilience in this current study.

Moreover, the PISA framework of student well-being (Borgonovi and Pál, 2016) covers the following five dimensions, cognitive, psychological, social, physical, and material well-being. This current study may cover four frameworks: the academic self-concept can be regarded as cognitive well-being, and the covariate mental illness is for psychological well-being. As for family and teacher support, those belong to the social well-being, and the covariate subsidy can measure the social-economic background of material well-being.

We implemented IRT models to (1) ensure the measurement materials are reliable and invariant and (2) estimate the person's latent trait level for the follow-up research (Cai, 2010; Muraki, 1992). Moreover, several studies showed similar research designs (Meulen *et al*., 2019; Zhang *et al.*, 2021).

Thus, we address the following three research questions (RQs):

- **RQ1.** According to the Masten model of resilience (Masten, 2001; Masten, 2014) with the academic-related outcome, to examine if the adolescent cases can fit the 4-group model for resilience theory by adjustment outcomes (academic self-concept) and risk factor levels. If not, then what kind of multiple-group model might be better?
- **RQ2.** What are the growth trends of academic self-concept and risk factors in the development of adolescents from 7- to 12-grade? Furthermore, to examine if the growth curves follow the developmental cascade or the Mattew effect. Besides, from the growth model, we can determine that academic resilience was more similar to a stable trait or a development process varying over time.
- **RQ3.** What are the effects of covariates, including gender, subsidy, mental illness, family support, and teacher support, on class membership, intercepts, and slopes?

The theoretical model of this current study is as **Figure 1**.

METHODOLOGY

Sample

The data used in this current study was obtained from the Taiwan database of children and youth in poverty (TDCYP) in wave 2011 (TFCF, 2014a), wave 2013 (TFCF, 2014b), wave 2015 (TFCF, 2017), and wave 2017 (TFCF, 2018), which was established by the Taiwan Fund for Children and Families (TFCF).

This database is based on foster children (under the age of 12) and adolescents (over the age of 12 and under the age of 18) replaced in foster family care, which have been

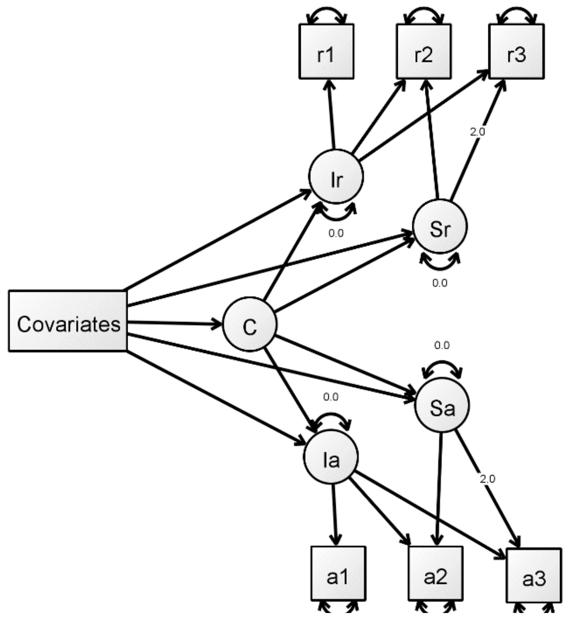

Figure 1. Two-part latent class growth model with covariates.
Note. (1) a1-a3 are academic self-concept scores across three time points. (2) I_a and S_a are the intercept and slope for academic self-concept. (3) r1-r3 are risk factor scores across three time points. (4) I_r and S_r are the intercept and slope for risk factors. (5) C is the latent classes. (6) Covariates include gender, subsidy, mental health, family support, and teacher support.

approved. Moreover, there are three primary types, (1) cases of abuse, neglect, abandoned babies, abandoned children, and street children, (2) cases from the court by law, and (3) other cases.

Although the target population of the TDCYP is not directly based on “social-economic disadvantaged” cases, the 2019 report of TFCF shows that 28.36% of the foster care cases were due to “financial difficulties and inability to support,” while the largest number of children were “abused or neglected,” at 59.58% in 2018.

The target population in this current study is who were in grades 7 and 8 (middle school) students at the first time point (T1); after two years, the same population grew up to grades 9 and 10 (middle and high school) students at the second time point (T2), and more two years later, they became grade 11 and 12 (high school) students at the third time point (T3), for covering the entire six-year secondary school ages. After combining the data of each wave by the same ID, we removed those students who had no response for at least one full scale to exclude those subjects who joined or left in the survey years, which is usually for longitudinal studies. Because the sample size that met the preceding criteria were not enough to be accepted, we collected two samples of the same age from the TDCYP database. Specifically, one sample was from the 2011 (baseline/T1), 2013 (T2), and 2015 (T3) surveys (N=452, 60.75%), and the other sample was from the 2013 (baseline/T1), 2015 (T2), and 2017 (T3) surveys (N=292, 39.25%). Notably, both the two samples contained 7/8, 9/10, and 11/12 grade students for the T1, T2, and T3, respectively.

The non-response rates of any single item of the whole over 90 items were far lower than 1%; the highest one (6 cases and 0.81% of no response) is in the item “Has your academic performance in the class improved or regressed compared to your previous education stage?” in the first time point. Moreover, the raw response data of scale are categorical; hence the median imputation rather than mean imputation was conducted to replace the trivial missing values.

In order to examine if the two samples were homogeneous, we conducted non-parametric Kolmogorov-Smirnov (KS) tests for the total score of the main measures. Most of the results of the KS tests, academic self-concept (D_{a1} = .05, p = .67, D_{a2} = .07, p = .41, D_{a3} = .07, p = .43), risk factor level (D_{r1} = .11, p = .02<.05, D_{r2} = .05, p = .66, D_{r3} = .18, p = <.001), mental illness (D = .04, p = .89), family support (D = .06, p = .64), and teacher support (D = .09, p = .10) were not significant, except for the risk factor level of the first and the third time point. We did not reject the two samples drawn from the same population. Therefore, we combined them as a data set with 744 subjects for the following-up analyses. Furthermore, the proportion of gender contains 361 boys

Table 1. Descriptive statistics and correlation based on IRT scores.

	ASC T1	ASC T2	ASC T3	Risk T1	Risk T2	Risk T3	Mental	Family	Teacher
ASC T1	-								
ASC T2	.61 ***	-							
ASC T3	.33 ***	.68 ***	-						
Risk T1	-.23 ***	-.19 ***	-.14 ***	-					
Risk T2	-.16 ***	-.20 ***	-.17 ***	.59 ***	-				
Risk T3	-.14 ***	-.21 ***	-.23 ***	.40 ***	.72 ***	-			
Mental	-.05	-.05	-.04	.37 ***	.29 ***	.22 ***	-		
Family	.21 ***	.20 ***	.14 ***	-.19 ***	-.15 ***	-.12 ***	-.18 ***	-	
Teacher	.25 ***	.22 ***	.14 ***	-.16 ***	-.15 ***	-.15 ***	-.08 *	.41 ***	-
M	-.09	-.002	.12	.09	-.23	-.48	.10	-.01	-.02
SD	.97	1.04	1.02	.85	.88	.93	.81	.94	.89

Note. ASC=Academic Self-Concept, Risk=Risk Factors, Mental=Mental Illness, Family=Family Support, Teacher=Teacher Support
**p*<.05. ***p*<.01. ****p*<.001.

(48.52%) and 383 girls (51.48%), as well as 225 no-subsidy (30.24%) and 519 low-/middle-subsidy (69.76%).

For all the 744 data, the gender proportion of boys (N=361, 48.5%) and girls (N=383, 51.5%), as well as subsidy proportion of no subsidy or no response (N=225, 30.2%), and low- or middle-income subsidy (N=519, 69.8%) for this current study are not significantly different (gender: $\chi^2_{(1)} = .38, p = .54$, subsidy: $\chi^2_{(1)} = 1.01, p = .31$) from the original sample of TDCYP. In other words, most of the adolescents in this data were in “poverty” or at least “near poverty.” Besides, the descriptive statistics and correlation of the response and explanatory variables are shown in Table 1. Except for the correlation coefficients of mental illness and three waves of academic self-concept, the other variables showed significance.

Figure 2 shows the range and quartiles for the nine variables. The range of most of them is between -3 and +3; that is because IRT transformation caused an effect similar to standard scores.

Measures

Background variable

Gender (0 = boy, 1 = girl) and subsidy (0 = no subsidy or no response, 1 = low- or middle-income subsidy) in TDCYP family background information and social worker questionnaire were included in this current study.

Academic self-concept

The general academic self-concept (T1-T3) items contain eight academic-related items (e.g., “Do you think that you study hard?”) for each time in the TDCYP self-report questionnaire 2 (for teenagers from middle school to college). The items have a four-point scale scoring from 1 to 4 (the options of each item are different but ordinal), including two reversed items, and across T1-T3 (2011, 2013 and 2015). The range of raw total scores of each wave is 8 to 32. In this current study, through a two-tier multidimensional (longitudinal) generalized partial credit model (GPCM) analysis, the goodness-of-fit indices are acceptable for M2 = 1715.98 (*df* = 253, *p* < .001), SRMR (standardized root mean square residual) = .15, RMSEA = .088 [.084, .092], CFI = .75, and MAP reliability indexes for T1, T2, and T3 are .79, .80, and .79.

Risk factors

The risk factors (T1-T3) of this current research were measured by a checklist obtaining 31 binary scoring questions for each time across T1-T3 (2011, 2013, and 2015). These items were collected from class events (“Have any of the following things happened in your class?” e.g., “Some classmates smoke”) and negative life events (“In the last 12 months, have any of the following things happened in your life?” e.g., “Family members are unemployed”) in TDCYP self-report questionnaire 2 (for teenagers). Four positive event items were removed from the life event checklist to measure the level of risk exposure. The raw score range of every single wave is from 0 to 31. This current study conducts a two-tier multidimensional (longitudinal) 2PL IRT analysis for the risk factors items. The model goodness-of-fit indices are good for M2=8617.36 (*df*=4271, *p*<.001), SRMR=.07, RMSEA=.037 [.036, .038], CFI=.78, and MAP reliability indexes for T1, T2, and T3 are .72, .72, and .70.

Mental illness

The mental illness (T1) was measured by the five-item brief-symptom rating scale (BSRS-5, Lee *et al.*, 2003) in the TDCYP self-report questionnaire 2 (for teenagers), which extracted five items from the original 50-item BSRS-

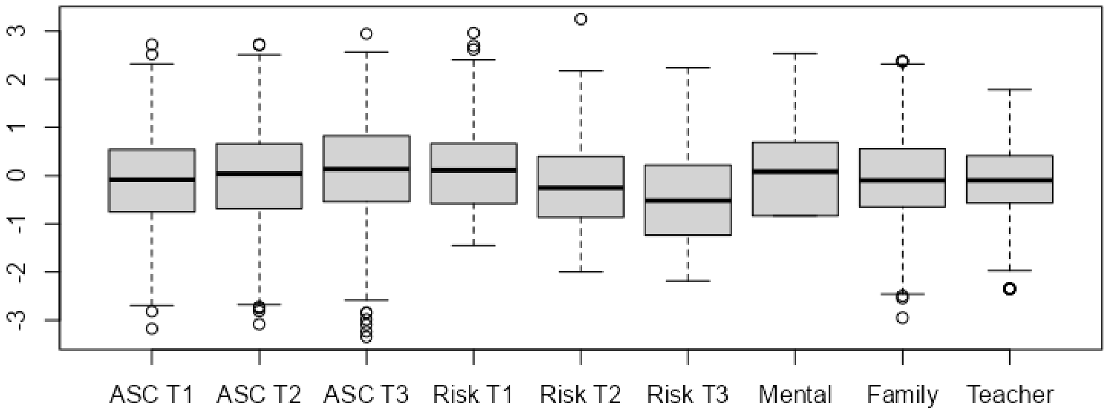

Figure 2. The range of each variable based on IRT scores.
Note. ASC=Academic Self-Concept, Risk=Risk Factors, Mental=Mental Illness, Family=Family Support, Teacher=Teacher Support.

50 (Lee *et al*., 1990), including anxiety (“Feeling tense or keyed up”), hostility (“Feeling easily annoyed or irritated”), depression (“Feeling blue or sad”), interpersonal hypersensitivity (“Feeling inferior to others”), and additional symptoms (“Trouble sleeping”). The Likert-type scale of five-point was used to score the BSRS-5, from 0 (“not at all”) to 4 (“extremely”). The BSRS-5 was designed for mental illness screening, so a cut-off score of 6 was included. If someone got a score of or above 6, they might have some emotional distress. Notice that in this current study, the item parameters (especially the discrimination) were estimated, causing the cutting point of mental illness would be a distribution with M=.70 and SD=.16 (range between .25 and 1.05), depending on the response to the different items. In addition, the results of the GPCM showed a good model-data fit for C2=12.29 (*df*=5, *p*=.03), SRMR=.03, RMSEA=.04 [.01, .08], CFI=.997, as well as the MAP reliability (T1) was .77.

Family support

The family support (T1) was measured by ten items about the relationship of family members being together (e.g., “Family members feel very close to each other.”) and three items of parental involvement (e.g., “Has your family ever participated in a parent-teacher conference?”) in the TDCYP self-report questionnaire 2 (for teenagers). The scoring is from 1 (strongly disagree) to 4 (strongly agree) for the former and 1 (never) to 4 (always) for the latter. Combing these two parts, the range of raw scores is between 13 and 52. In this current study, the MAP reliability (T1) is .91 from the GPCM, which showed a nice model-data fit C2=172.01 (*df*=39, *p*<.001), SRMR=.05, RMSEA=.07 [.06, .08], CFI=.91.

Teacher support

Three items about school teachers measured the teacher support (T1) (e.g., “The school teachers are very concerned about me”) in the TDCYP self-report questionnaire 2 (for teenagers). It is a Likert-type scale with four points (1=strongly disagree to 4=strongly agree), and the raw scores are from 3 to 12. In this current study, the MAP reliability (T1) is .80 from the GPCM, which showed a nice model-data fit C2=10.74 (*df*=2, *p*=.005), SRMR=.03, RMSEA=.08 [.04, .12], CFI=.99.

Data analysis

Item response models

The item response models were applied to estimate an individual’s latent trait level for the precisely measured goal of this person-focused study. There are several benefits of using IRT rather than factor analysis in the total-score approach (Andrich and Marais, 2019; Gorter *et al*., 2015). Although the 1PL/Rasch measurements have some excellent properties, the fitting performance (fit indices and reliability indexes) of the 2PL/GPCM models was always better than those of the 1PL/Rasch models. Thus, the two-tier 2PL/GPCM IRT model (Cai, 2010) was conducted for longitudinal data (academic self-concept and risk factor), as well as the other cross-section data fitted the GPCM (Muraki, 1992) under single-dimensional constructs in this current study.

Binary data, such as the risk factor measured in this current study, usually does not follow the normal distribution. Moreover, the response from a Likert-type scale is theoretically categorical data. Thus, IRT can help with these data properties in a logistic-like model. For longitudinal data, Gorter *et al.* (2015) have proven that IRT can deal with the variance problems in repeated measurement better than the other sum-scores approaches based on CTT. Furthermore, the IRT model can ensure measurement invariance across different time points through constrained item parameters. Indeed, IRT measurements have been used in international large-scale

Table 2. Fit indices and LR test for latent class growth models.

Model	#par	AIC	BIC	aBIC	Entropy	*p*LMR	*p*BLRT	min N
1-class	10	12185.63	12231.75	12199.99	-	-	-	744
2-class	15	11539.44	11608.62	11560.99	.74	<.001	<.001	307
3-class	20	11339.10	11431.34	11367.83	.69	.14	<.001	212
4-class	25	**11103.83**	**11219.13**	**11139.74**	.73	**.14**	**<.001**	**132**
5-class	30	11113.83	11252.19	11156.92	**.77**	.14	<.001	0

Note. #par=number of parameters, AIC= Akaike information criterion, BIC= Bayesian information criterion, aBIC= sample-size adjusted BIC, *p*LMR=the *p*-value of Lo-Mendell-Rubin likelihood ratio test, *p*BLRT= the *p*-value of bootstrap likelihood ratio test, min N=number of people in the minimum class.

assessments and patient-report of medical research (Gorter *et al*., 2015) for a long while. Therefore, the present research conducted IRT models for estimating every person's trait level for follow-up analyses.

The raw data and IRT trait level still showed a high correlation, including the academic self-concept T1 (.96), T2 (.96), and T3 (.97), the risk factors T1 (.95), T2 (.93), T3 (.93), the mental illness T1 (.95), the family support T1 (.98), and the teacher support T1 (.98). The former information can eliminate the concern of whether the IRT scores are different from the raw data and thus cause statistical artifacts. For estimating personal trait level, there are three primary methods in IRT, maximum likelihood (ML), maximum a posteriori (MAP), and expected a posteriori (EAP). In this current study, we selected the MAP estimates as personal trait level because the ML would fail with the all endorse/not endorse response pattern, and the EAP would bias in the multidimensional factor structures (Embretson and Reise, 2000).

Latent class growth model (LCGM)

The latent class growth model (LCGM) is a particular case of the latent growth mixture model (LGMM), which is a helpful framework integrating person- and variable-centered longitudinal methods (Muthén and Muthén, 2000), but fixed the variances of intercept and slope factors as zero (Jung and Wickrama, 2007). In contrast, the original LGMM estimates the variances of both intercept and slope factors. However, after conducting LGMMs in this current study, we found that original LGMMs could not show acceptable results for class selection. Also, the probabilities of the classes and the parameter estimates changed noticeably when the covariates were added. Eventually, we constrained the variance estimates of the intercept and slope factors to zero as LCGMs, which were better for model selection and explanation.

We followed the five steps by Jung and Wickrama (2007) to build our LCGM in this current study. (1) specified a single-class latent growth curve model and (2) an unconditional latent class model without covariates. We presented the earlier two steps together within the third step. Furthermore, this study obtained only three waves of data. Thus, we only considered a linear model instead of a quadratic and cubic model. We reported the results that (3) determined the number of classes as Table 2, then we (4) checked the convergence issues since the class sizes and parameter estimates generated using different random seeds did not differ considerably. Eventually, we (5) specified a conditional latent class model with covariates, and the results were reported in Figure 3 and Table 3 to Table 5.

In particular, for examining the adversity situation (risk factors) and positive outcomes (academic self-concept) simultaneously, we specified a two-part LCGM, like the previous studies (Bowers and Sprott, 2012; McGinley *et al*., 2016; Muthén, 2006; Wu *et al*., 2010; Yampolskaya *et al*., 2015). Nevertheless, we did not split a variable into binary and continuous parts but indicated two independent variables in a single model.

Tools

The data processing and analyses were mainly conducted using R language version 4.1.3 (R Core Team, 2022). For IRT, the R-package mirt version 1.36.1 (Chalmers, 2012) was used for GPCM and two-tier IRT with MH-RM and EM algorithms, respectively. For LCGM, the R-package MplusAutomation version 1.1.0 (Hallquist and Wiley, 2018) was used based on the Mplus version 7.11 (Muthén and Muthén, 1998-2012) for statistical computing but had a more familiar syntax to the R environment. In addition, the MLR estimator was used for calibrating the parameters of LCGM.

RESULTS

Masten model of resilience (RQ1)

First, the number of classes had to be determined. Thus, we tried one- to five-class unconditional two-part LCGM models to obtain both academic self-concept and risk factors and then compared their fit indices, including the number of parameters, Akaike information criterion (AIC),

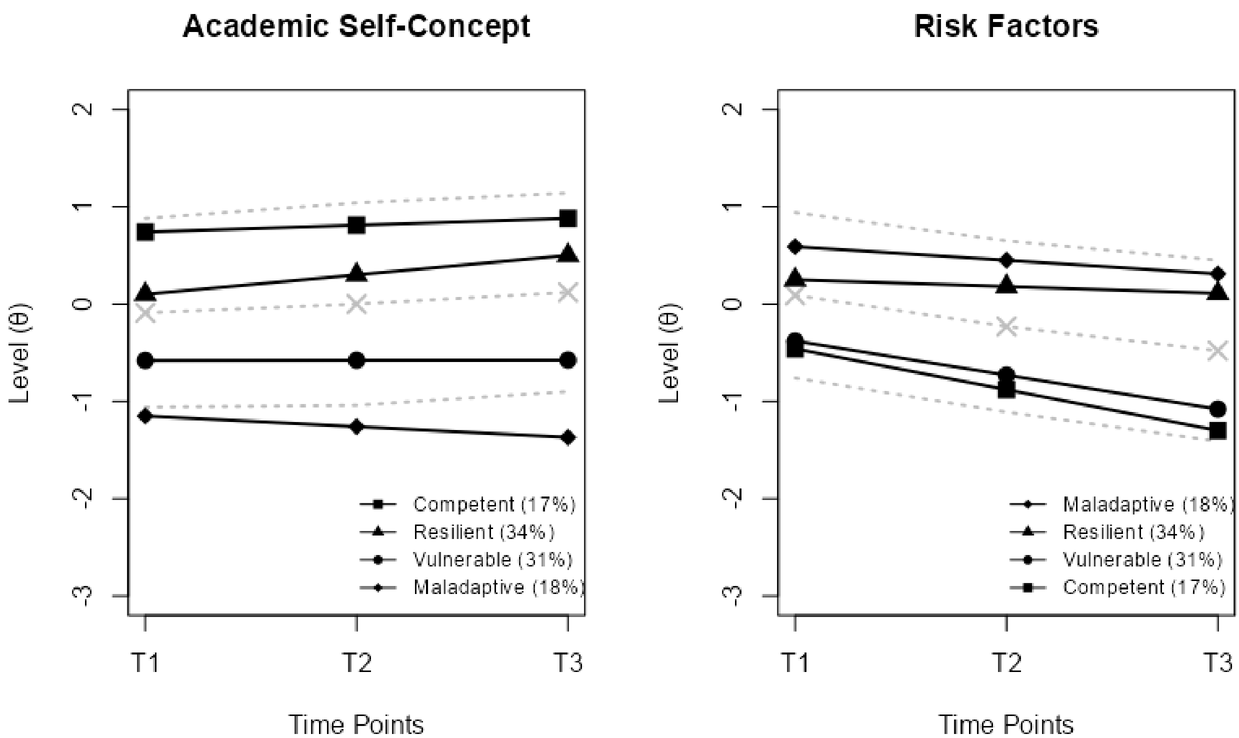

Figure 3. Trajectories of academic self-concept and risk factors level with covariates.
Note. The interval of dashed lines is the mean of observed data and the M±1*SD.

Table 3. Growth factor parameter estimates for the four-class conditional LCGM.

		Resilient	Competent	Vulnerable	Maladaptive
Academic self-concept					
Intercept	Est. (SE)	0.10 (.18)	0.74 (.30)	-0.58 (.25)	-1.15 (.23)
	t	0.55	2.44*	-2.33*	-4.93***
Slope	Est. (SE)	0.02 (.06)	0.07 (.07)	0.002 (.06)	-0.11 (.10)
	t	0.37	1.06	0.04	-1.09
Risk factor					
Intercept	Est. (SE)	0.25 (.12)	-0.46 (.12)	-0.38 (.13)	0.59 (.17)
	t	2.10*	-3.82***	-2.89**	3.55***
Slope	Est. (SE)	-0.07 (.05)	-0.42 (.07)	-0.35 (.06)	-0.14 (.08)
	t	-1.40	-6.18***	-5.62***	-1.83
Prob.		.34	.17	.31	.18

Note. *p<.05. **p<.01. ***p<.001. Prob=based on estimated posterior probabilities.

Bayesian information criterion (BIC), sample-size adjusted BIC (aBIC), entropy, the p-value of Lo-Mendell-Rubin likelihood ratio test (*p*LMR), the p-value of bootstrap likelihood ratio test (*p*BLRT), and the number of people in the minimum class. Where AIC, BIC, and aBIC are better as possible as small, the larger entropy means the model contains more information, and the *p*LMR and *p*BLRT are better for close to zero, which means the significance of the difference between the former and later models. In conclusion, the four-class model was selected in this current study for the smaller AIC, BIC, and aBIC, acceptable entropy, minimum class population, and significant *p*BLRT (Table 2).

After choosing the four-class model, we need to name

Table 4. Covariate prediction of trajectory class membership.

Variable	Resilient		Competent		Vulnerable	
	OR	95% CI	OR	95% CI	OR	95% CI
Gender	.51	[.19, 1.33]	.33	[.08, 1.42]	.58	[.22, 1.50]
Subsidy	.58	[.23, 1.47]	1.08	[.17, 6.72]	1.21	[.49, 2.97]
Mental (T1)	1.42	[.89, 2.27]	1.48	[.63, 3.48]	1.03	[.48, 2.17]
Family (T1)	1.01	[.62, 1.66]	1.00	[.45, 2.21]	1.16	[.65, 2.07]
Teacher (T1)	.48**	[.29, 79]	.35*	[.15, .80]	.48*	[.24, .95]
Intercept	4.53*	[1.24, 16.54]	1.68	[.15, 19.17]	2.39	[.91, 6.24]

Note. The maladaptive class served as the referent. OR=odds ratio of a variable effect on the other class compared to the maladaptive class. (i.e., other class/maladaptive class). Gender (0=boy), Subsidy (0=No)
**p*<.05. ***p*<.01. ****p*<.001.

the groups and give them meaning from resilience theories. Recall the Masten model, and the four groups may be (1) the competent group with reasonable adjustment and low adversity, (2) the resilient group with reasonable adjustment but high adversity, (3) the vulnerable group with poor adjustment but low adversity, and (4) the maladaptive group with poor adjustment and high adversity. According to the location estimates of academic self-concept and risk factors for the four groups (Table 3), we named the groups that correspond to the above properties.

Growth of academic self-concept and risk (RQ2)

Table 3 shows the estimates of intercept and slope factors of both academic self-concept and risk factors. For academic self-concept, all the slopes of the four classes are not significant but intercept. That is, we can expect the growth curve of academic self-concept might be four lines close to horizontal but at clearly different locations (Figure 3). Specifically, the highest one is the competent class (Est.=.74, *t*=2.44, *p*=.02<.05), then the order is the resilient class (Est.=.10, *t*=.55, *p*=.58), vulnerable (Est.=-.58, *t*=-2.33, *p*=.02<.05), and maladaptive class (Est.=-1.15, *t*=-4.93, *p*<.001). For risk factors, the slopes of the competent class (Est.=-.42, *t*=-6.18, *p*<.001) and vulnerable class (Est.=-.35, *t*=-5.62, *p*<.001) are significant, in other words, only these two groups showed a remarkable decreasing trend (Figure 3). Moreover, the intercepts of risk factors are significantly different from zero, and even more important, and they are also appropriate to the assumptions of the Masten model. We can indicate the higher risk exposure groups as maladaptive (Est.=.59, *t*=3.55, *p*<.001) and resilient (Est.=.25, *t*=2.10, *p*=.04<.05), as well as the lower groups as vulnerable (Est.=-.38, *t*=-2.89, *p*=.004<.05) and competent (Est.=-.46, *t*=-3.82, *p*<.001). Finally, the posterior probabilities based on the estimates are .34, .17, .31, and .18 for the resilient, competent, vulnerable, and maladaptive classes, respectively.

Figure 3 shows the trajectories of the four groups on academic self-concept and risk factors levels. Because our study had only three-time points unsuitable for adding a quadratic even cubic slope factor in the growth model, these curves all look like straight lines. Except for the curves of latent means, we still drew the mean and the interval of ±1 standard deviation of the total sample of 744 subjects to understand the relative position of groups in contrast to the sample.

Explanatory effects of covariates (RQ3)

Table 4 shows covariates’ effects (odds ratio, OR) on predicting the class members when the other variables were controlled. Because the “latent class membership” response variable was a categorical variable with four choices, the model would like a multinomial logistic regression. If the *OR*> 1, meaning the probability of classifying a subject to the control (resilient, competent, or vulnerable) class has a higher probability than the reference (maladaptive) class, and vice versa. The parameters in Table 4 are almost not significant, but only the teacher support of resilient (*OR*=.48, *p*=.004<.05), competent (*OR*=.35, *p*=.01<.05), and vulnerable (*OR*=.48, *p*=.04<.05) to the maladaptive group are significant. Specifically, suppose the other variables were controlled. At the same time, the teacher support increased one logit (IRT θ estimates), and the probability of a student classifying into the resilient group would decrease by 52% (1-.48) than into the maladaptive group. Similarly, the probability of a student classifying into the competent group would decrease by 65% (1-.35), and into the vulnerable group would decrease by 52% (1-.48), in contrast to the maladaptive group.

Table 5 shows the effects of predictors of gender, subsidy, mental illness, family support, and teacher support on the growth factors. For academic self-concept, only family support (Est.=.15, *t* = 2.44, *p*=.02<.05) and teacher support (Est.=.37, *t* = 6.33, *p*<.001) had significant positive effects on the baseline, as well as the gender (Est.=.22, *t* =4.81, *p*<.001) had a significant positive effect on the growth factor. Where gender is binary data, the growth of girls (gender=1) would be more apparent than

Table 5. Covariate prediction of intercepts and slopes.

Variable	Intercept		Slope	
	Est. (SE)	t	Est. (SE)	t
Academic self-concept				
Gender	.23 (.13)	1.77	.22 (.05)	4.81***
Subsidy	.04 (.17)	.22	-.01 (.05)	.81
Mental (T1)	-.11 (.06)	-1.73	-.02 (.03)	.42
Family (T1)	.15 (.06)	2.44*	-.02 (.02)	.40
Teacher (T1)	.37 (.06)	6.33***	-.03 (.03)	.22
Risk factors				
Gender	-.02 (.09)	-.21	-.15 (.04)	-3.75***
Subsidy	.08 (.11)	.73	.04 (.05)	.82
Mental (T1)	.36 (.08)	4.45***	-.06 (.03)	-1.91
Family (T1)	-.07 (.06)	-1.27	.04 (.02)	1.47
Teacher (T1)	-.18 (.07)	-2.76**	-.04 (.03)	-1.31

Note. *p<.05. **p<.01. ***p<.001.

that of boys (gender=0). For risk factors, only mental illness (Est.=.36, t = 4.45, p<.001) and teacher support (Est.=-.18, t = -2.76, p=.01<.05) had significant effects on the baseline, as well as the gender (Est.=-.15, t =-3.75, p<.001) had negative a significant effect on the growth factor. In other words, the student who had some mental symptoms or with less teacher care would simultaneously have high associated risk factors. Likewise, the boys would have more chance of growth on risk factors than the girls. Some values in Table 5, although they do not meet a significant level of $\alpha = .05$ still met a significant level of $\alpha = .10$ hence worthing notice. They were the gender effect (Est.=.23, t=1.77, p=.077<.10) and the mental health effect (Est.=-.11, t=-1.73, p=.084<.10) on the intercept of academic self-concept, and the mental health effect (Est.=-.06, t=-1.91, p=.056<.10) on the slope of risk factor.

DISCUSSION

The primary purpose of this current study was to implement a method to investigate academic resilience with the positive outcome (academic self-concept) and risk factors (adverse life events) simultaneously, as well as the associations among the growth trend, classes, and covariates. Hence, we conducted a conditional latent class growth modeling to examine the former research topics. The study contributed that the four-class resilience model was feasible for the TDCYP data, but no significant growth trends for academic self-concepts. That is to say, the initial state of the academic self-concept determined the trait level of a student's academic self-concept for the entire secondary school age. Moreover, the support from family and teachers had significant help for the initial state of academic self-concept. Besides, gender and mental illness had slight effects, too.

Academic resilience model (RQ1)

First, The Masten model (Masten, 2001, 2014; Masten *et al.*, 1999) of resilience was examined in this study. We measured the growth trend of academic self-concept and risk factors simultaneously, and the results showed that the latent structure of the four classes was the better model.

Since the latent class analysis (person-centered method) is exploratory, the resilience structure might vary depending on the sample. Similar classification results have been reported in parents of children with cancer (Luo *et al.*, 2022), with depressive symptoms and distinct trajectories of psycho-social functioning after First-Episode Psychosis (FEP) (Salagre *et al.*, 2020). However, the related studies did not always yield this four-class result (Lines *et al.*, 2020; Mammarella *et al.*, 2018). Future research could consider a confirmatory approach for latent class/profile if this four-group structure is more specific.

The important thing is that we can compare different groups by the same advertising conditions, such as the resilient group vs. the maladaptive group, to identify what features caused the different adaption outcomes (academic self-concept).

Stable development of academic resilience (RQ2)

Second, the trajectories showed stability. We conducted an LCGM with three-wave longitudinal data to explore the *process of change* of resilience. However, the results showed no significant growth trend in academic self-concept and risk factors (resilient and maladaptive group). The results implied two things, (1) the academic self-concept of disadvantaged Taiwanese students might fix at the beginning of secondary school. Moreover, (2) the risk factors declined in the at-slight-risk group (competent group and vulnerable group) rather than the at-risk groups (resilient and maladaptive group) at T1. This implied a cumulative effect (or developmental cascades, Matthew effect) (Masten *et al.*, 2005). The results are similar to the psychological resilience of police officers (Meulen *et al.*, 2019).

Besides, this current study aims to identify the class model of resilience, but more detailed comparisons have not been carried out for different groups. Future works can investigate the features that help the resilient group maintain its positive trajectory.

Related and protective factors (RQ3)

Third, we found that gender is a critical factor that can interpret intercept and slope growth factors of academic self-concept. However, poverty did not significantly affect this current study, and it might be inferred that most subjects in TDCYP are from socioeconomically disadvantaged families. Thus, the poverty condition is homogeneous in this study.

For the initial effect of protective factors, mental health (illness) is a critical variable. It caused the location of academic self-concept and both location and growth slope of risk factors. Call for the PISA research (Agasisti *et al.*, 2018; Borgonovi and Pál, 2016), and this study may reflect the generalized well-being framework. For caring adults, the effect of family support is smaller than expected. This may be due to the properties of the data, as with the poverty variable (subsidy). However, we found that teacher support has a deterministic impact, regardless of classifying the trajectory memberships or the location of adaption and risk factors. It is worth further studying that school-based context how to support a student, especially the socioeconomically disadvantaged.

CONCLUSION AND RECOMMENDATIONS

Eventually, we summarized the findings of this current study. (1) The study confirmed Masten's four-class resilience model is suitable for describing academic resilience. (2) The development of academic resilience of socioeconomically disadvantaged Taiwanese students is not a time-varying change in the entire middle school ages. (3) Gender, mental health (illness), and teacher support play critical roles in this current study, and they could explain the development trends of academic resilience.

This study used academic self-concept rather than academic achievement for measuring academic resilience. Although most academic resilience scales adopted the concept near academic self-concept (Cassidy, 2016; Martin, 2013; Tudor and Spray, 2017), academic achievement can reflect objectivity. Besides, there were only three waves contained in this study. Thus, we only built linear trajectory models for this data rather than a quadratic or cubic curve model. If future works could obtain data with much more effective time points, they might figure out different development types.

Moreover, in TDCYP data, we only focused on the socioeconomically disadvantaged students. For this reason of data properties, we could not identify the effects from family or poverty/SES because of the homogeneity. Future works could try to explore the SES-related effects on academic resilience.

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