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Developmental Asset Profiles and Longitudinal Transitions in Chinese Middle School Students: A Latent Profile and Transition Analysis

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Abstract

Background: Developmental assets, the supportive relationships and personal strengths that promote healthy development, are consistently associated with adolescents' school adjustment, yet less is known about how these assets cluster within individuals and how these patterns change over time.

Methods: This study used a person-centered approach to identify developmental asset profiles among Chinese middle school students, examine transitions between profiles over a school year, and test associations with family socioeconomic status (SES) and academic adaptation.

Results: Latent profile analysis of 23 asset indicators in a cross-sectional sample (N = 2,393; Grades 7–8) identified three profiles that differed mainly in overall level: high-asset (19%), moderate-asset (50%), and low-asset (31%). Random-intercept latent transition analysis in a separate longitudinal sample (N = 1,095) assessed in September, December, and March showed that the high-asset profile was the most stable from T1 to T2 (.68) but less so from T2 to T3 (.51). About two fifths of moderate-asset students moved to the low-asset profile in each interval, whereas roughly half of low-asset students moved to a higher profile. Higher SES was associated with membership in higher-asset profiles and with upward rather than downward transitions. The profiles differed markedly in learning strategy use and academic well-being (high > moderate > low) whereas academic-achievement differences across profiles were small, and students whose profile membership improved over the school year reported better academic adaptation than those whose membership declined.

Conclusions: Developmental asset profiles in early adolescence appear to be changeable, and moderate-asset

students warrant particular attention in prevention efforts.

Keywords: developmental assets, positive youth development, latent profile analysis, latent transition analysis, academic adaptation

Introduction

Early adolescence is a period of rapid biological, cognitive, and social change, and for most students it coincides with the move into secondary school [1, 2]. Middle school typically offers less personal contact with teachers, places greater emphasis on grades and social comparison, and gives peers a larger role in students' lives [3, 4]. In China, these changes coincide with intensifying competition as students approach the senior high school entrance examination at the end of Grade 9. A poor fit between adolescents' needs and these demands has been linked to declining grades, motivation, and engagement [3, 5, 6]. We use the term *academic adaptation* to refer to how well students meet the demands of schooling in terms of performance, learning behavior, and emotional experience. Because academic adaptation in these years predicts later achievement, well-being, and educational attainment [7, 4], identifying the resources that support it is of both theoretical and practical importance.

The developmental assets framework, developed within the positive youth development (PYD) perspective, offers a strength-based account of why some adolescents do well in school while others struggle [8, 9, 10]. PYD theory proposes that thriving emerges from mutually beneficial relations between individual strengths and the resources of the surrounding ecology rather than from the mere absence of risk [11, 12]. The framework distinguishes external assets, the supports, relationships, and opportunities provided by families, schools, peers, and communities, from internal assets, personal qualities such as commitment to learning, positive values, social competence, and a positive identity [9, 10]. Cross-sectional and longitudinal studies have consistently linked more assets to better academic, psychological, and behavioral outcomes [13, 10]. Research with Chinese adolescents shows a similar pattern: cumulative assets predicted fewer concurrent and subsequent externalizing behaviors [14], and school assets were associated with more favorable patterns of psychosocial adaptation over time [15].

Internal assets overlap considerably with the attributes studied in PYD research; self-efficacy, for example, is an internal asset in the assets framework and an indicator of confidence in the PYD literature. The two traditions differ mainly in emphasis: the assets framework treats these qualities as resources that promote later development, whereas PYD research often treats them as indicators of thriving [16, 12]. Because our interest lies

in what these qualities contribute to adaptation, we refer to them as internal assets. Most research on PYD attributes has adopted the Five Cs model of competence, confidence, connection, character, and caring [12], but culturally grounded models have also been proposed for Chinese adolescents. Shek et al. [17] developed a scale assessing 15 PYD constructs in Hong Kong, and in mainland China, Lin et al. [18] used interview data to define PYD as the competence, character, and self-worth shown by adolescents who are developing healthily and fully; Chai et al. [19, 20] then developed and validated a scale based on this model.

This model, which we used to assess internal assets, comprises four domains: character (love, aspiration, integrity, and perseverance), competence (academic, social-emotional, and life skills), confidence (positive feelings about and evaluations of oneself), and connection (a sense of belonging to and acceptance by family, school, and community; [18, 21]). Several of these qualities, such as filial piety (part of love) and aspiration, reflect values that are strongly emphasized in Chinese families and schools and are not explicitly represented in the Five Cs model.

For external assets, we drew on ecological systems theory [19] and focused on the family and the school, the two microsystems in which middle school students spend most of their time. We considered three sources of assets (parents, teachers, and peers) and four aspects of each: relationship quality, that is, the closeness a student feels toward the parent, teacher, or peer [20]; emotional support, which conveys care and acceptance; instrumental support, which provides concrete help such as materials, guidance, or advice [20]; and autonomy support, which encourages students to think and act independently rather than directing their behavior [22, 23]. Relationship quality and support are conceptually distinct but closely linked in practice, because close relationships are usually the channels through which support is provided. Crossing the three sources with the four aspects yielded 12 external asset indicators, which, together with the 11 internal asset subdimensions, constituted the 23 indicators used in this study.

Connection and external support should be distinguished. Support refers to what parents, teachers, and peers provide, whereas connection refers to the student's own sense of belonging, which develops through repeated interactions with them. The two are related but not interchangeable: a student may receive help from teachers and nonetheless feel that he or she does not belong at school.

The assets framework further assumes that assets are cumulative, that external and internal assets interact

(support from parents and teachers strengthens confidence and competence, and confident, capable students make better use of the support available to them; [1]), and that healthy development depends on a breadth of assets rather than on any single one [24, 9, 10]. The last two assumptions imply that the function of a given asset depends on the other assets a student has, which is a reason to study assets in combination rather than one at a time.

Assets also tend to co-occur. Students with strong support at home often report good peer relationships and higher self-efficacy, whereas disadvantaged students frequently lack resources in several domains at once, a pattern that parallels the clustering of risk factors in cumulative risk research [25, 26]. If assets cluster in this way, their joint contribution may depend on how they are configured within the individual rather than on their sum. Most studies, however, have used variable-centered methods, which estimate average associations across a sample and assume that they hold for all individuals [27, 28]. Such methods cannot show whether subgroups of students have qualitatively different asset configurations or whether similar outcomes arise from different configurations. Person-centered methods address these questions by identifying subgroups of individuals with similar patterns across multiple indicators [28, 29].

A second limitation of previous research is its reliance on cross-sectional designs. Assets change as family circumstances, school contexts, peer relationships, and adolescents' own capacities change [11, 30]. Longitudinal data are therefore needed to establish which students maintain a stable level of assets, which gain or lose assets, what predicts these changes, and whether such changes are related to adaptation. The last of these questions has received the least attention, even though it bears directly on how interventions should be designed and where resources should be directed.

A growing number of person-centered studies have begun to address these issues. Using data from 10,997 Australian 15-year-olds, Burns et al. [31] identified five profiles of intrapersonal and interpersonal psychosocial resources that were associated with different levels of achievement. In China, Hou et al. [15] used latent transition analysis to show that students with more school assets were less likely to move from a well-adapted profile to an externalizing or peer-rejection profile, and Chai et al. [32] examined trajectories of PYD and their promotive factors across the transition to senior high school.

Several questions nonetheless remain open. First, person-centered studies have typically examined either

internal assets or PYD attributes alone; few have combined external assets from the family, school, and peer group with internal assets in a single model. Doing so would provide a more complete picture of students' resources and more specific guidance for intervention [31]. Second, longitudinal studies have mostly linked profile transitions to general PYD or to problem behavior, and less is known about how transitions relate to academic adaptation, the outcome of greatest concern to schools. Third, although SES is known to shape access to developmental resources [33, 34, 35], it remains unclear how SES relates to profile membership and to movement between profiles over time.

We addressed these questions using complementary cross-sectional and longitudinal samples. Latent profile analysis (LPA) was used in the larger cross-sectional sample to identify asset configurations; it is appropriate when multiple continuous indicators are available and no established typology exists [29, 36]. Random-intercept latent transition analysis (RI-LTA) was then used in the longitudinal sample to model movement between profiles. Unlike conventional latent transition analysis, which tends to overestimate the probability of remaining in the same profile, RI-LTA includes a random intercept that absorbs stable between-person differences in the indicators, so that trait-like differences are not mistaken for stability in profile membership (Muthén [37, 38]). We asked (a) what developmental asset profiles can be identified among Chinese middle school students and how prevalent each is; (b) how stable profile membership is over the school year, how SES, grade, and gender relate to profile membership, and how SES relates to transitions; and (c) how profiles and transitions relate to academic achievement, learning strategy use, and academic well-being.

Given that assets tend to accumulate and co-occur, we expected the profiles to differ primarily in overall asset level (Hypothesis 1), although we also examined whether profiles with uneven combinations of external and internal assets would emerge. Conservation of resources theory holds that people with more resources are better able to protect and expand them, whereas those with fewer resources are more vulnerable to further loss [39]. We therefore expected the high-asset profile to be the most stable and higher SES to be associated with membership in, and transitions toward, higher-asset profiles (Hypothesis 2). Grade and gender were examined as additional covariates; on the basis of stage–environment fit theory [3], we expected eighth graders to be less likely than seventh graders to belong to higher-asset profiles. Finally, we expected academic adaptation to be best in the high-asset profile and poorest in the low-asset profile, and students whose profile membership improved over time to show better adaptation than students whose membership declined (Hypothesis 3).

Method

Participants

Two samples were used. Sample 1, which was used to identify asset profiles, consisted of 2,393 students in Grades 7 and 8 from 57 classes in 12 middle schools in eastern, central, and western China (51.0% boys; age range = 11–15 years, M = 12.9 years, SD = 0.62). A stratified random sampling procedure was used: schools were stratified by location (urban vs. suburban), and classes were randomly selected within each stratum.

Sample 2, which was used for the longitudinal analyses, was recruited by cluster random sampling from 32 Grade 7 and Grade 8 classes in middle schools in eight provinces and municipalities in China. In the Chinese system, Grade 7 is the first year of junior high school (typically ages 12–13) and Grade 8 is the second (ages 13–14). Students were assessed three times at intervals of approximately 3 months: in September (T1), December (T2), and the following March (T3). Of the 1,226 students who participated at T1, 1,095 (89.3%) completed all three assessments and constituted the analytic sample (52.3% boys; Mage = 12.8 years, SD = 0.70). Students who completed all three assessments did not differ from those lost to attrition in age, $t = -0.44$, $p = .66$; family SES, $t = -1.07$, $p = .29$; only-child status, $\chi^2(1) = 0.15$, $p = .70$; or gender, $\chi^2(1) = 2.26$, $p = .13$.

The study was approved by the institutional ethics committee. School administrators and parents gave consent before data collection, students were told that participation was voluntary and that they could withdraw at any time, and questionnaires were group-administered in classrooms by trained administrators using standardized instructions.

Measures

Developmental Assets. External assets were measured with three parallel scales referring to parents (13 items), teachers (12 items), and peers (13 items), each assessing relationship quality (closeness), emotional support (e.g., feeling cared for and appreciated), instrumental support (e.g., receiving help with problems), and autonomy support (e.g., being encouraged to think and decide independently). Relationship quality (intimacy subscale) and emotional and instrumental support items were adapted from the Chinese version of the Network of Relationships Inventory (NRI; [20]; [40]), and autonomy support items from the student version of the parental autonomy support measure used by Wang et al. [23]. Teacher and peer versions were created by changing the referent of the parent items. Items were rated on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*).

Internal assets were measured with a 48-item short form of the Chinese Positive Youth Development Scale [21, 41], which covers four domains with 12 items each: character (love, aspiration, integrity, and perseverance), competence (academic ability, social-emotional ability, and life skills), confidence, and connection (family, school, and community connection). The scale was developed for Chinese adolescents and validated in a large national sample. Items were rated on a 5-point scale (1 = *not at all true*, 5 = *completely true*).

Academic Adaptation. Academic achievement was measured with three items asking students to evaluate their overall academic standing in class (e.g., "What is your academic level in your class?") on a 7-point scale (1 = *very poor*, 7 = *very good*); self-reported grades and class ranks converge substantially with school records, although less so among lower-achieving students [42]. Learning strategy use was measured with a nine-item short Chinese version of the Motivated Strategies for Learning Questionnaire (MSLQ; [43, 44]), with three items each for cognitive, metacognitive, and resource management strategies. Academic well-being was measured with a nine-item scale adapted from Shek and Chai [45] on the basis of the three-component model of subjective well-being [46], covering satisfaction with learning, positive learning experiences, and negative learning emotions (reverse scored). Both scales were rated from 1 (*strongly disagree*) to 5 (*strongly agree*). The three measures index the performance, behavioral, and affective components of academic adaptation.

Family Socioeconomic Status. Family SES was assessed following Shi and Shen [47] on the basis of parents' educational attainment and occupational status; in Sample 2, household income was also recorded. Higher scores indicate higher SES.

Psychometric Properties. Scales originally developed in English were translated and back-translated [48]. In Sample 1, confirmatory factor analyses (CFAs) showed acceptable fit for the external asset scales (CFI = .91, TLI = .90, RMSEA = .06, SRMR = .04), the internal asset scale (CFI = .94, TLI = .93, RMSEA = .08, SRMR = .04), the learning strategy scale (CFI = .97, TLI = .96, RMSEA = .06, SRMR = .03), and the academic well-being scale (CFI = .96, TLI = .93, RMSEA = .08, SRMR = .05); Cronbach's alphas exceeded .80 for each external asset scale and were .96 for internal assets, .87 for academic achievement, .93 for learning strategies, and .84 for academic well-being. For Sample 2, Table 1 reports occasion-specific CFAs, internal consistency, and tests of longitudinal measurement invariance conducted with the lavaan package in R [49]. Fit was acceptable at each occasion, although the CFIs and TLIs for external assets were slightly below .90. Using ΔCFI < .010 and

ΔRMSEA < .015 as criteria [50, 51], metric and scalar invariance held for external assets, learning strategies, and academic well-being; for internal assets, metric invariance held and full scalar invariance did not (ΔCFI = .018), but partial scalar invariance was supported, so the measures can be regarded as comparable across occasions. In Harman's single-factor test, the first unrotated factor accounted for 21.03% of the variance in Sample 1 and for 21.17%–27.04% across occasions in Sample 2, suggesting that common method variance was not a dominant source of covariation, although this test cannot rule out method bias [52].

Table 1 *Occasion-Specific Model Fit, Internal Consistency, and Longitudinal Measurement Invariance*

Measure	Occasion	CFI	TLI	RMSEA	SRMR	α
Panel A: Occasion-specific confirmatory factor analyses						
External assets	T1	.899	.892	.063	.046	.950
	T2	.892	.885	.061	.045	.957
	T3	.897	.889	.066	.046	.956
Internal assets	T1	.956	.946	.058	.040	.965
	T2	.954	.944	.077	.038	.968
	T3	.948	.935	.080	.040	.968
Learning strategy use	T1	.976	.968	.06	.026	.936
	T2	.966	.956	.077	.03	.944
	T3	.966	.957	.075	.03	.943
Academic well-being	T1	.989	.965	.059	.03	.841
	T2	.989	.965	.062	.029	.845
	T3	.991	.971	.056	.029	.847
Academic achievement	T1	—	—	—	—	.683
	T2	—	—	—	—	.844
	T3	—	—	—	—	.848
Panel B: Longitudinal measurement invariance						
Measure	Model	$\Delta\chi^2$	Δdf	ΔCFI	ΔRMSEA	Supported
External assets	Metric	52.19	70	.001	.000	Yes
	Scalar	74.82	70	.000	.009	Yes
Internal assets	Metric	23.06	24	.000	.003	Yes
	Scalar	209.42***	24	.018	.007	No
	Partial scalar	17.36	10	.006	.003	Yes
Learning strategy use	Metric	12.15	18	.000	.004	Yes
	Scalar	18.13	18	.000	.003	Yes
Academic well-being	Metric	19.32	12	.006	.007	Yes
	Scalar	34.56***	12	.003	.004	Yes

Note. N = 1,095. T1 = September; T2 = December; T3 = March. Panel A reports confirmatory factor analyses

conducted separately at each occasion and Cronbach's α. The academic achievement model (three items) is just-identified and was therefore not evaluated for fit or invariance. In Panel B, metric models were compared with configural models, and scalar and partial scalar models with metric models; ΔCFI and ΔRMSEA are absolute changes. Because χ^2 difference tests are sensitive to sample size, invariance decisions were based on ΔCFI < .010 and ΔRMSEA < .015 rather than statistical significance of $\Delta\chi^2$ [50, 51].

***$p < .001$.

Data Analysis

Latent profile and transition analyses were conducted in Mplus 8.3 using robust maximum likelihood (MLR) estimation. Because students were nested within classes, standard errors were adjusted for clustering (TYPE = COMPLEX). Analyses were based on complete data (listwise deletion); in Sample 2, the analytic sample consisted of the 1,095 students who completed all three assessments. Listwise deletion yields unbiased estimates when data are missing completely at random [53], and the attrition analyses reported above showed no differences between completers and noncompleters on the demographic variables examined.

LPA models with one to five profiles were estimated in Sample 1 (N = 2,393), with indicator means freely estimated and variances constrained to be equal across profiles. Following current recommendations [36, 54], we compared models using the Akaike information criterion (*AIC*) and the sample-size-adjusted Bayesian information criterion (*aBIC*), with lower values indicating better fit; the adjusted Lo–Mendell–Rubin likelihood ratio test (aLMR) and the bootstrapped likelihood ratio test (BLRT), which compare a k-profile model with a (k − 1)-profile model; and parsimony and interpretability. Because these indices often continue to favor additional profiles in large samples [29], we also considered the rate at which the information criteria decreased and the size of the smallest profile. Entropy was used to describe classification accuracy (≥ .80 indicating good accuracy) but not to select the number of profiles.

In Sample 2, LPAs were first estimated separately at each occasion to check that the same number of profiles was supported at T1, T2, and T3. Transitions from T1 to T2 and from T2 to T3 were then modeled with a three-profile RI-LTA (Muthén [37, 38]), in which all indicators load on a continuous random intercept factor that captures stable between-person differences in overall asset level, so that the transition probabilities reflect within-person change. Profile-specific indicator means were constrained to be equal across occasions, so that the profiles had the same meaning at each occasion, and residuals of the same indicator were allowed to correlate across occasions. A transition probability is the probability of belonging to a given profile at time t + 1, conditional on

membership in a particular profile at time t.

In Sample 1, the associations of SES, grade (0 = Grade 7, 1 = Grade 8), and gender (0 = boy, 1 = girl) with profile membership were estimated with the R3STEP procedure (Asparouhov & Muthén [55]), which corrects for classification error; all three pairs of profiles were compared, with a Bonferroni-adjusted significance level of .017. In Sample 2, for students in a given profile at time t, membership at time t + 1 was regressed on SES in multinomial logistic regressions with remaining in the same profile as the reference category, so that an odds ratio (*OR*) above 1 indicates that higher SES was associated with greater odds of moving to a given profile rather than staying.

In Sample 1, profile differences in academic adaptation were tested with the BCH method [56, 57], which accounts for classification uncertainty, using omnibus Wald χ^2 tests followed by pairwise Wald tests with Bonferroni-adjusted *p* values. In Sample 2, students were grouped by their sequence of profile membership across the three occasions (e.g., low → moderate → high). Sequences shown by fewer than 15 students were excluded, and the remaining sequences were compared on a composite academic adaptation score (the sum of the standardized scores for achievement, learning strategy use, and well-being) with a one-way analysis of variance (ANOVA) and Tukey's honestly significant difference (HSD) tests.

Results

Latent Profile Analysis

The LPA was based on the 23 asset indicators. Fit statistics for models with one to five profiles are presented in Table 2. *AIC* and *aBIC* decreased with each additional profile, but the decrease was largest up to three profiles and diminished thereafter (*aBIC* decreased by 22,040 from one to two profiles, 7,577 from two to three, 3,392 from three to four, and 2,378 from four to five). The aLMR favored the three-profile over the two-profile model ($p < .001$) and the four-profile over the three-profile model ($p = .003$) but not the five-profile over the four-profile model ($p = .119$), and the BLRT was significant for every comparison and thus did not discriminate between solutions. The three-profile solution showed high classification accuracy (entropy = .93), and all three profiles were of substantial size (19%–50%), whereas the four- and five-profile solutions each included a profile containing 13% of the sample. Weighing the diminishing gains in fit against parsimony and interpretability, we retained the three-profile solution.

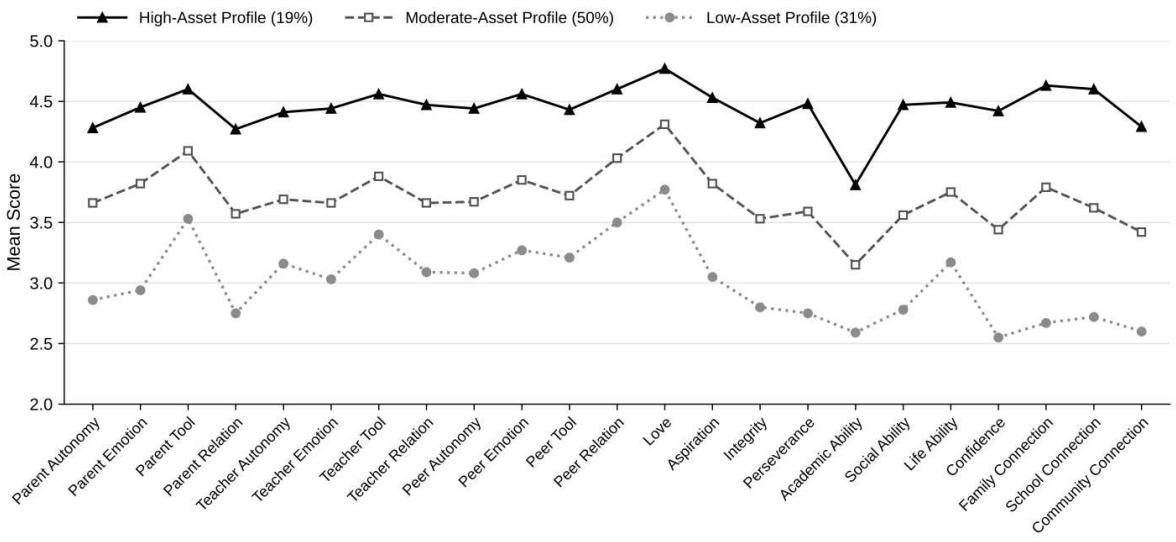
Table 2 *Model Fit Indices for Latent Profile Models With One to Five Profiles*

Profiles	*LL*	*k*	*AIC*	*aBIC*	Entropy	aLMR *p*	BLRT *p*	Proportions
1	−85,961.07	60	172,042.15	172,198.33	—	—	—	1.00
2	−74,869.46	91	149,920.92	150,157.90	.94	< .001	< .001	.54/.45
3	−71,009.64	122	142,263.28	142,580.86	.93	< .001	< .001	.31/.50/.19
4	−69,242.09	153	138,790.17	139,188.44	.92	.003	< .001	.18/.37/.33/.13
5	−67,981.73	184	136,331.42	136,810.42	.92	.119	< .001	.17/.23/.17/.30/.13

Note. N = 2,393. The retained three-profile solution is shown in bold. *LL* = log-likelihood; *k* = number of free parameters; *AIC* = Akaike information criterion; *aBIC* = sample-size-adjusted Bayesian information criterion; aLMR = adjusted Lo–Mendell–Rubin likelihood ratio test; BLRT = bootstrapped likelihood ratio test. The aLMR and BLRT compare each model with the model with one fewer profile. Dashes indicate statistics that are not applicable.

The three profiles are shown in Figure 1. The high-asset profile (19%) had high means on nearly all indicators, from 3.81 (academic ability) to 4.77 (love), and above 4.25 on every indicator except academic ability. The moderate-asset profile (50%) had intermediate means, from 3.15 (academic ability) to 4.31 (love), and the low-asset profile (31%) had the lowest mean on every indicator, from 2.55 (confidence) to 3.78 (love). The profiles differed primarily in overall level rather than in shape, and no profile with an uneven combination of external and internal assets emerged. The gap between the high- and low-asset profiles was largest for family connection (1.96 scale points), school connection (1.89), confidence (1.87), perseverance (1.73), social-emotional ability (1.70), and community connection (1.69), and smallest for love (1.00), instrumental support from parents (1.08), and relationship quality with peers (1.09).

Figure 1 *Developmental Asset Profiles Across 23 Dimensions*



Note. Values are profile means on the 1–5 response scale. Percentages indicate profile prevalence in Sample 1 (*N* = 2,393).

Latent Transition Analysis

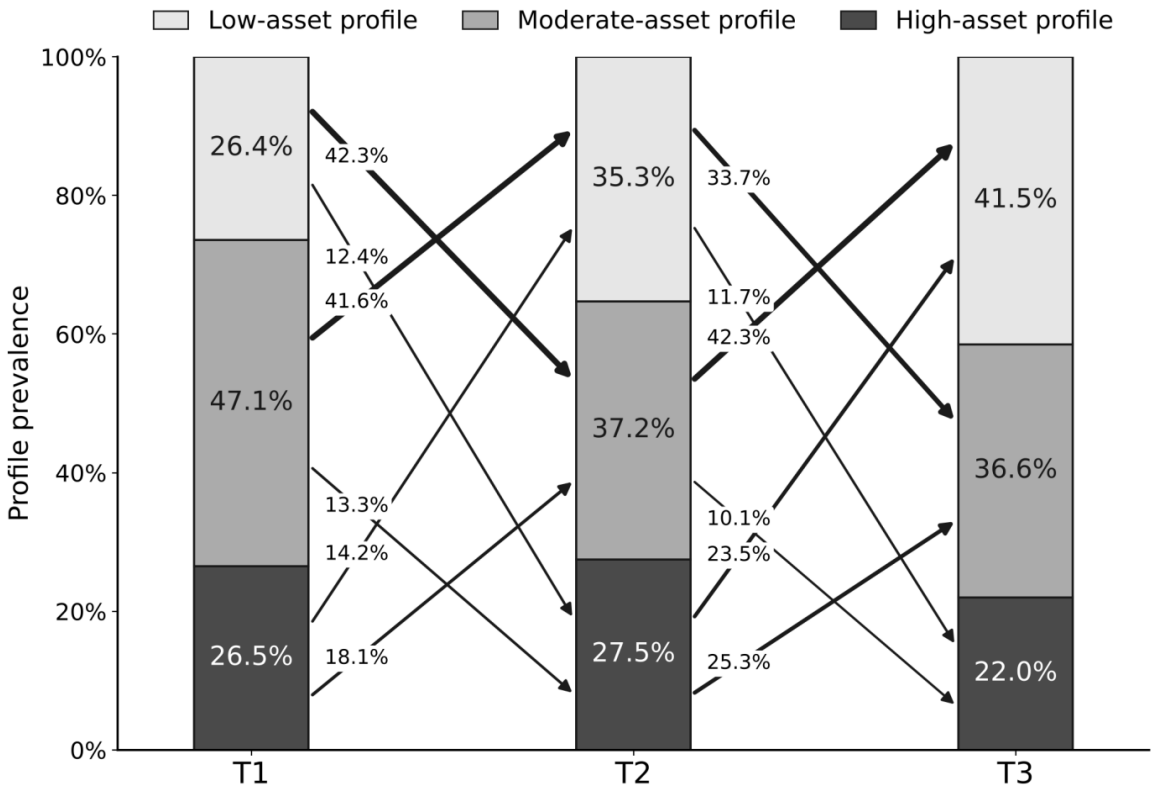
In Sample 2, separate LPAs at each occasion supported three profiles at T1, T2, and T3: the three-profile models showed good classification accuracy (entropies ≥ .90), and both the aLMR and the BLRT favored them over two-profile models (*ps* < .05). The three-profile RI-LTA classified students with acceptable accuracy (entropy = .84). The estimated T1 prevalences of the low-, moderate-, and high-asset profiles were 26.4%, 47.1%, and 26.5%; combining them with the transition probabilities in Table 3 yields model-implied prevalences of 35.3%, 37.2%, and 27.5% at T2 and 41.5%, 36.6%, and 22.0% at T3 (Figure 2). The T1 prevalences differ from those in Sample 1, which may reflect sample differences as well as the joint estimation of profile membership across occasions in the RI-LTA.

Table 3 *Profile Transition Probabilities of Developmental Assets Across Three Measurement Occasions*

	T1 → T2			T2 → T3		
Profile at time *t*	Low	Moderate	High	Low	Moderate	High
Low-asset	.453	.423	.124	.546	.337	.117
Moderate-asset	.416	.451	.133	.423	.476	.101
High-asset	.142	.181	.677	.235	.253	.512

Note. Rows indicate profile membership at time *t* and columns indicate membership at time *t* + 1. Entries are conditional transition probabilities; values on the diagonal (in bold) indicate stability. T1 = September; T2 = December; T3 = March.

Figure 2 *Profile Transitions Across Three Measurement Occasions*



Note. Bars show profile prevalences in Sample 2 (*N* = 1,095): estimated prevalences at T1 and model-implied prevalences at T2 and T3, obtained from the T1 prevalences and the transition probabilities in Table 3. Percentages may not sum to 100 because of rounding. Arrows show transitions between different profiles, and arrow width is proportional to the transition probability. Stability probabilities are reported in Table 3.

From T1 to T2, the high-asset profile was the most stable: 67.7% of these students remained in it, 18.1% moved to the moderate-asset profile, and 14.2% moved to the low-asset profile. Stability was considerably lower in the moderate-asset (45.1%) and low-asset (45.3%) profiles. Among moderate-asset students, 41.6% moved down to the low-asset profile, whereas among low-asset students, 42.3% moved up to the moderate-asset profile and 12.4% to the high-asset profile.

A different pattern emerged from T2 to T3. Only 51.2% of high-asset students remained in that profile; 25.3% moved to the moderate-asset profile and 23.5% to the low-asset profile. Stability in the moderate-asset profile increased slightly to 47.6%, but 42.3% of these students again moved to the low-asset profile. In the low-asset profile, stability increased from 45.3% to 54.6%, and the proportion moving up to the moderate-asset profile decreased from 42.3% to 33.7%. Membership in the low-asset profile thus became more persistent as the school year progressed.

Academic Adaptation Outcomes

Academic achievement showed little overall variation across profiles. The high-versus-low pairwise comparison yielded Wald $\chi^2(1) = 2.76$, with a mean difference of 0.06 points on the 7-point scale (4.95 vs. 4.89; Table 4).

Table 4 *Academic Adaptation by Developmental Asset Profile*

	Academic achievement	Learning strategy	Academic well-being
Profile means, *M* (*SE*)			
Low-asset	4.89 (0.02)	2.60 (0.02)	2.00 (0.02)
Moderate-asset	4.92 (0.03)	3.14 (0.02)	2.54 (0.02)
High-asset	4.95 (0.03)	3.80 (0.03)	3.23 (0.03)
Wald χ^2 tests			
Omnibus (*df* = 2)	3.2	1,166.12***	1,258.80***
Low vs. moderate (*df* = 1)	0.69	437.73***	374.49***
Low vs. high (*df* = 1)	2.76	1,116.01***	1,238.90***
Moderate vs. high (*df* = 1)	0.5	371.80***	417.35***

*Note***.** *N* = 2,393. Means are BCH-estimated, with standard errors in parentheses. Academic achievement was rated on a 7-point scale; learning strategy use and academic well-being on 5-point scales. Pairwise *p* values were Bonferroni adjusted. *$p < .05$. ***$p < .001$.

In Sample 2, a total of 12 sequences involving a change in profile membership were observed; six were shown by fewer than 15 students and were not analyzed. In the analysis of academic adaptation for the remaining six sequences (n = 353), three were upward (low → high → high, moderate → high → high, and low → moderate → high) and three were downward (high → moderate → low, moderate → moderate → low, and moderate → low → low). Adaptation differed across sequences, $F(5, 347) = 4.82$, $p < .001$, $\eta^2 = .06$, and Tukey HSD tests indicated that each upward sequence was associated with better adaptation than each downward sequence ($ps < .05$). Adaptation was highest among students who moved from the low- to the high-asset profile between T1 and T2 and stayed there (n = 35) and lowest among those who moved from the moderate- to the low-asset profile between T1 and T2 and stayed there (n = 73). Because assets and adaptation were measured over the same period, these results describe associations, and reciprocal influences are likely.

Covariates of Profile Membership and Transitions

In Sample 1, SES, grade, and gender were entered simultaneously as predictors of profile membership

(Table 5). Higher SES was associated with greater odds of belonging to the moderate-asset rather than the low-asset profile (*OR* = 1.18, 95% *CI* [1.05, 1.33], $p = .005$) and, more strongly, to the high-asset rather than the low-asset profile (*OR* = 1.71, 95% *CI* [1.42, 2.05], $p < .001$) or the moderate-asset profile (*OR* = 1.45, 95% *CI* [1.29, 1.63], $p < .001$). Each one-unit increase in SES was thus associated with 71% higher odds of belonging to the high-asset rather than the low-asset profile.

Compared with seventh graders, eighth graders had 42% lower odds of belonging to the moderate-asset rather than the low-asset profile (*OR* = 0.58, 95% *CI* [0.50, 0.67], $p < .001$) and 36% lower odds of belonging to the high-asset rather than the low-asset profile (*OR* = 0.64, 95% *CI* [0.52, 0.79], $p < .001$), but grade did not distinguish the high- from the moderate-asset profile (*OR* = 1.11, 95% *CI* [0.88, 1.40]). Gender was not associated with profile membership in any comparison (all 95% CIs included 1).

Table 5 *Associations of SES, Gender, and Grade With Profile Membership in Sample 1*

	Moderate vs. low		High vs. low		High vs. moderate	
Predictor	*OR*	95% *CI*	*OR*	95% *CI*	*OR*	95% *CI*
SES	1.18*	[1.05, 1.33]	1.71***	[1.42, 2.05]	1.45***	[1.29, 1.63]
Gender	0.90	[0.75, 1.08]	0.81	[0.65, 1.01]	0.90	[0.73, 1.11]
Grade	0.58***	[0.50, 0.67]	0.64***	[0.52, 0.79]	1.11	[0.88, 1.40]

Note. The second profile in each comparison is the reference category. SES = family socioeconomic status; gender was coded 0 = boy, 1 = girl; grade was coded 0 = Grade 7, 1 = Grade 8. OR = odds ratio; CI = confidence interval. Significance was evaluated against Bonferroni-adjusted thresholds for three comparisons. *$p < .0167$. ***$p < .0003$.

In Sample 2, SES was associated with transitions in both intervals (reference category: remaining in the same profile). From T1 to T2, among students in the high-asset profile, higher SES was associated with lower odds of moving to the moderate-asset profile (*OR* = 0.68, $p = .03$) and to the low-asset profile (*OR* = 0.53, $p = .022$); among students in the low-asset profile, higher SES was associated with higher odds of moving to the moderate-asset profile (*OR* = 1.80, $p = .015$) and to the high-asset profile (*OR* = 1.53, $p = .022$). From T2 to T3, among students in the moderate-asset profile, higher SES was associated with higher odds of moving to the high-asset profile (*OR* = 1.58, $p = .024$) and lower odds of moving to the low-asset profile; among students in the low-asset profile, higher SES was associated with higher odds of moving to the moderate-asset profile (*OR* = 2.22, $p < .05$) and to the high-asset profile (*OR* = 1.43, $p < .05$). Students from higher-SES families were therefore more likely to move up and less likely to move down.

Discussion

Asset Profile Heterogeneity and Stability

This study examined the configuration, short-term dynamics, and academic correlates of developmental assets among Chinese middle school students. Consistent with Hypothesis 1, three profiles emerged, high-asset (19%), moderate-asset (50%), and low-asset (31%), and they differed mainly in overall asset level rather than in the relative standing of particular asset domains.

The predominance of level-differentiated profiles agrees with research showing that advantages and disadvantages tend to co-occur [25, 26], and such co-occurrence may widen differences between students over time through processes of cumulative advantage [58]. Within this overall pattern, the profiles were separated most clearly by students' sense of connection and by their confidence, and least by love and by instrumental support from parents, which were relatively high even in the low-asset profile. A sense of belonging and a positive view of oneself may therefore be the internal assets most sensitive to the overall level of support that students experience. Because no profile with an uneven configuration emerged, the present data do not show that particular combinations of assets matter beyond their overall amount. A student with strong family support but weak peer relationships and low self-efficacy might fare worse than an additive model would predict, but such configurations were not common enough to form a separate profile in this sample, and larger or more heterogeneous samples are needed to examine them.

Hypothesis 2 was partly supported. In the first interval, the high-asset profile was the most stable (67.7%), consistent with conservation of resources theory [39]: students with many assets can draw on them when difficulties arise, maintain their relationships, and keep building skills. In the second interval, however, its stability fell to 51.2%, slightly below that of the low-asset profile (54.6%), and roughly a quarter of high-asset students moved to each of the lower profiles, so even a well-resourced position offered only partial protection as the school year progressed. Instability also meant different things in the other two profiles. Moderate-asset students who changed profiles mostly moved down (41.6% and 42.3% moved to the low-asset profile in the two intervals); they appear to have sufficient resources under ordinary conditions but not enough to buffer them when demands increase, in line with the proposition that people with fewer resources are more vulnerable to further loss. Low-asset students who changed profiles, by contrast, mostly moved up.

At the sample level, the model-implied prevalence of the low-asset profile rose from 26.4% at T1 to 41.5% at T3, whereas that of the high-asset profile fell from 26.5% to 22.0%. This downward shift is consistent with stage–environment fit theory, which predicts declines in perceived support and motivation when school environments become more competitive and less personal just as adolescents' need for autonomy and close relationships grows [3]; the heavier academic load and end-of-year examinations of the second semester may have intensified these pressures. Because the study covered only 6 months, however, seasonal fluctuations cannot be ruled out.

Low-asset students were more likely to move up in the first interval than in the second (42.3% vs. 33.7% to the moderate-asset profile), and more of them remained in the low-asset profile in the second interval (54.6% vs. 45.3%). Even so, about half of low-asset students moved to a higher profile in each interval (54.7% and 45.4%, counting moves to either the moderate- or the high-asset profile). Asset levels in early adolescence therefore appear to be far from fixed, and support from schools, families, or peers may help students improve their position within a relatively short time.

Socioeconomic Status, Profile Dynamics, and Educational Equity

Consistent with Hypothesis 2, SES was associated both with profile membership and with transitions: students from higher-SES families were more likely to belong to the higher-asset profiles, more likely to move up, and less likely to move down. This finding agrees with ecological and social capital accounts, which hold that SES shapes development through material and educational investment, access to well-resourced schools and programs, and social networks that provide emotional and practical support [33, 59, 60].

These results have implications for educational equity. School social capital partly accounts for the association between family SES and PYD [35], suggesting that schools can partly compensate for family disadvantage. Our findings indicate, however, that SES-related differences in assets may persist or widen without intervention: students from low-SES families were less likely both to belong to the higher-asset profiles and to move into them, so school-based programs that reach disadvantaged students across several asset domains are likely to be needed.

As expected, eighth graders were less likely than seventh graders to belong to the higher-asset profiles, which is consistent with evidence that relationships with teachers become less close as students progress through

secondary school while academic pressure and the need for autonomy increase [3, 4]. Because grade was compared cross-sectionally, the difference may also reflect cohort or school differences. Gender was unrelated to profile membership, suggesting that any gender differences in specific assets were not large enough to produce different overall configurations.

Asset Profiles and Academic Adaptation

Hypothesis 3 was partly supported. The profiles differed substantially in learning strategy use and academic well-being, with gaps of more than one scale point between the high- and low-asset profiles on both measures. Assets thus appear to be closely tied to how students engage in learning and how they feel about it, consistent with the view that supportive relationships and personal strengths sustain motivation, effective strategy use, and positive emotions in learning [1, 4].

Self-rated academic achievement showed little overall variation across profiles (omnibus Wald $\chi^2(2) = 3.20$; Table 4). The high-asset group mean was 4.95 ($SE = 0.03$), compared with 4.89 ($SE = 0.02$) in the low-asset group, a difference of 0.06 points on the 7-point scale. The high-versus-low pairwise Wald statistic was 2.76. The adjusted *p* value and all achievement contrasts should be confirmed against the original analysis output before inferential conclusions are drawn.

In Sample 2, students whose profile membership improved over the school year reported better adaptation than students whose membership declined, and students who moved directly from the low- to the high-asset profile and stayed there reported the best adaptation of all sequences examined. These findings are consistent with the view that development in early adolescence remains malleable [11] and with Rutter's [61] concept of turning points. Because assets and adaptation were measured over the same period, however, they do not show that gains in assets caused better adaptation; intervention studies are needed to test whether strengthening several asset domains improves adaptation within a school term.

Implications for Practice

The findings suggest several implications for schools. First, routine assessment of developmental assets could help identify students who need support and match support to need, with universal programs for all students, targeted programs for moderate-asset students at risk of decline, and more intensive support for low-asset students. Nearly one third of the cross-sectional sample belonged to the low-asset profile, and in the longitudinal

sample this share rose from about one quarter to two fifths over 6 months. Second, because more than 40% of moderate-asset students moved to the low-asset profile in each interval, this group deserves more attention than it usually receives; these students may appear to be doing well but seem to lack the reserves needed to cope with rising academic demands, and supporting them before they decline may be more effective than intervening afterward.

Third, the SES findings suggest that universal programs alone are unlikely to reduce disparities in assets, and schools serving low-income communities may need additional resources for mentoring, tutoring, peer support, family engagement, and counseling. Fourth, because assets in different domains co-occurred, programs that address several domains at once (family–school partnerships, teacher–student and peer relationships, and students' own skills and self-efficacy) may be more effective than single-domain programs, a possibility that should be tested directly. Finally, identifying what changed for students who moved from the low- to the high-asset profile within a single interval could show which forms of support, such as intensive mentoring, help with schoolwork, or greater family involvement, are most likely to produce broad improvements.

Limitations and Future Directions

Several limitations should be considered. First, both samples consisted of urban and suburban students, and the findings may not generalize to rural students, ethnic minority students, or other cultural contexts. Second, the longitudinal assessment covered only 6 months, and longer follow-up, ideally across all three years of junior high school, is needed to determine whether the transitions represent lasting change or short-term fluctuation. The longitudinal analyses were also restricted to students who completed all three assessments; although completers and noncompleters did not differ on the demographic variables examined, listwise deletion yields biased estimates if attrition was related to unmeasured characteristics [53]. In addition, profiles were identified in one sample and their transitions examined in another, and in Sample 1 the aLMR favored a four-profile solution that we did not retain; future studies should examine whether the same three profiles, or an additional smaller profile, emerge when both analyses are based on the same sample.

Third, assets and academic outcomes were all self-reported, so shared method variance may have inflated their associations, and academic achievement was measured with students' ratings of their standing in class rather than with examination scores or school records; this relative self-evaluation may also be influenced by the school-

comparison processes described in research on academic self-concept [62]. Self-report is appropriate for perceived support and well-being, but future studies should include reports from parents and teachers and objective indicators of achievement.

Fourth, we did not examine the mechanisms through which SES is related to assets. Material resources, parenting practices, educational investment, and social networks are all plausible pathways, and future studies should test them as mediators to identify the most promising targets for intervention.

Finally, the study was observational. Randomized trials of programs targeting several asset domains, with profile membership, transitions, and adaptation as outcomes, are needed to test whether changing students' assets improves their adaptation and to determine the intensity such programs require.

Conclusion

Using LPA and RI-LTA, this study identified three developmental asset profiles among Chinese middle school students (high-asset, 19%; moderate-asset, 50%; low-asset, 31% in the cross-sectional sample) that differed in stability and in patterns of transition over 6 months of a school year. Family SES was associated with profile membership and transitions between profiles. The profiles differed markedly in learning strategy use and academic well-being, whereas self-rated academic-achievement means were similar across profiles (4.89–4.95 on the 7-point scale; omnibus Wald $\chi^2(2) = 3.20$). Students whose profile membership improved over time reported better academic adaptation than those whose membership declined. The observed changes in profile membership suggest that developmental assets may be malleable during middle school, although the observational design does not establish causality.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki. The research protocol was approved by the Institutional Review Board / Ethics Committee of Hunan Police Academy (approval No. 20260802). Informed consent was obtained from all individual participants included in the study. For participants under the age of 18, written informed consent was also obtained from their parents or legal guardians.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data in any form (e.g., personal details, images, or videos).

Availability of data and materials

The data presented in this study are available on request from the corresponding author (Qiang Zhou, 656403178@qq.com).

Competing interests

The authors declare that they have no competing interests.

Author Contributions

Conceptualization, J.H. and Z.J.; methodology, J.H. and Y.T.; software, J.H.; validation, J.H., Z.J., and Y.W.; formal analysis, J.H. and Y.T.; investigation, J.H., Y.W., and Q.Z.; resources, Z.J. and Y.T.; data curation, J.H. and Y.W.; writing−original draft, J.H.; writing−review and editing, Z.J., Y.T., and Y.W.; visualization, J.H.; supervision, Z.J.; project administration, Z.J. and Q.Z.; funding acquisition, Z.J. All authors have read and agreed to the published version of the manuscript.

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