

Ability Versus Action Self-Efficacy as Differential Predictors of Learning Engagement among Chinese Top-Up Degree Students

Xinyu Hu¹, Wei Li^{2*}

¹Beijing College of Finance and Commerce, Beijing 101101, China

²College of Applied Science and Technology, Beijing Union University, Beijing 100012, China

*Corresponding author: Wei Li, nanliwei325@163.com

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Abstract: We compared ability self-efficacy (confidence in academic ability) and action self-efficacy (confidence in carrying out study strategies) as predictors of learning engagement in a cross-sectional survey of Chinese top-up degree students. Items were adapted from a Chinese learner-characteristics scale to fit the top-up degree context. Of 363 collected questionnaires, 25 straight-line or invariant responses were removed, leaving 338 for analysis. Confirmatory factor analysis fit a three-factor measurement model well, and chi-square difference tests kept the three constructs separate despite their high latent correlations. A common method bias check suggested that no single factor explained the covariance among the indicators. In the structural model, ability self-efficacy predicted engagement significantly ($\beta = 0.685$, $P < 0.001$); action self-efficacy did not ($\beta = 0.197$, $P = 0.097$). A Wald test separated the two coefficients on the unstandardized scale ($z = 6.71$, $P < 0.001$) but reached only marginal significance on the standardized scale ($z = 2.03$, $P = 0.043$). The model explained 73.1% of the variance in engagement. On balance, confidence in academic capability emerges as the more proximal driver of engagement, though the standardized gap between the two dimensions was small.

Keywords: Ability self-efficacy; Action self-efficacy; Learning engagement; Structural equation modeling; Top-up degree students

Online publication: September 30, 2026

1. Introduction

For a vocational college graduate in China, the main road to a bachelor's degree runs through the top-up program. The degree does more than add a credential. It opens jobs that the entrance exam had closed off, it builds graduates' competence and career prospects, and it promotes equity in higher education for students who came up through the vocational track. The move is not smooth. Students step from a practice-oriented

vocational curriculum into an academically demanding university, often on a tight schedule. They also arrive from many different vocational colleges, each with its own standards, so their starting points are far less even than those of regular undergraduates.

That unevenness matters for how we study the psychological processes behind academic engagement. Self-efficacy—what students believe they can do—is a core resource students draw on as they adapt to the academic demands of this transition ^[1,2].

In Bandura's ^[3] formulation, self-efficacy is a person's belief that they can organize and carry out the actions needed to reach a given level of performance. Social cognitive theory places this belief near the center of motivation and effort—and, over time, persistence. Students who believe they can do the work exert greater effort and persist longer, and use better study strategies ^[4]. The link to learning engagement ^[5] holds across educational levels and cultures, with meta-analytic effects in the moderate-to-large range ^[2,6]. It is not, however, the same everywhere: Multon *et al.* ^[4] found the predictive power of self-efficacy shifting with the outcome and with who was being studied.

The link is well established. The inside of the construct—how self-efficacy breaks into parts—has drawn less attention. Bandura ^[7] argued that efficacy should be measured at the level of the specific domain, and that different dimensions do different work. Bong and Skaalvik ^[8] split academic self-efficacy (confidence in understanding the content) from self-regulatory efficacy (confidence in running the study strategies). We follow a version of that split. Ability self-efficacy is confidence that one can grasp and master the coursework. Action self-efficacy is confidence in carrying out concrete learning actions—picking out the key points, budgeting study time, choosing methods that work. We chose the two labels to mark the order of the learning process: a student first has to believe the material is within reach, and only then does the question of study techniques arise.

The split matters because the two dimensions may not predict engagement equally. A student who doubts their basic ability faces one kind of problem; a student who trusts their ability but doubts their study habits faces another. Whether these two problems carry different weights for engagement has not been directly tested in this population. Bong and Skaalvik ^[8] noted that an efficacy dimension can carry more or less weight depending on the learner. Bandura ^[9] acknowledged that self-efficacy's function is situation-sensitive even as he defended its general predictive power. That tension is exactly what we address here, by setting the two dimensions against each other as predictors of engagement.

Pajares ^[1] reviewed the evidence that self-efficacy predicts differently across domains and student groups. Most of that work, though, treats self-efficacy as one thing, or looks at its parts one at a time rather than comparing their predictive weight for engagement ^[1,2,4]. For top-up degree students, then, the ability–action distinction is theoretically important and rarely tested.

We take up the question with Chinese top-up degree students. In a structural equation model, engagement is regressed on both efficacy dimensions at once, so the two weights can be compared directly. The question is whether ability self-efficacy predicts engagement more strongly than action self-efficacy, as the ability–action distinction implies.

The answer bears on where universities put their support. If ability self-efficacy is the stronger predictor, then building students' confidence in their academic capability may be more effective than strategy training alone. Knowing which dimension weighs more would help direct support resources—with the caveat that cross-sectional, correlational data cannot settle questions of cause.

We ask two questions. First, do ability and action self-efficacy differ in how strongly they predict engagement among top-up degree students? Second, does that difference survive when we switch to an alternative, composite-score specification?

Social cognitive theory and earlier evidence of dimension differentiation lead to one hypothesis. H1: Ability self-efficacy predicts learning engagement more strongly than action self-efficacy.

2. Methods

2.1. Participants

We collected data through a paper-based survey of students in top-up degree programs at a public university in China. These programs let vocational college graduates finish a bachelor's degree after transferring to a university.

Of 363 responses, we dropped 25 for straight-line or invariant answering within a dimension, leaving 338 valid cases.

The sample was 138 men (40.8%) and 200 women (59.2%). Most were first-year students ($n = 311$, 92.0%); the other 27 were second-year (8.0%). Majors spanned accounting (27.2%), management (27.2%), tourism management (15.7%), computer science and related fields (11.2%), English (11.8%), finance (4.1%), business administration (0.9%), and other fields (1.8%).

2.2. Measures

All items used a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). We built the self-efficacy items from the learner-characteristics scale of Wang and Fu^[10], which contains a self-efficacy dimension validated among Chinese online learners. We then adapted those items to the top-up degree context: we rewrote the wording to match the academic demands of the vocational-to-university transition, and we wrote new items to operationalize the ability–action distinction drawn from social cognitive theory^[3,7] and from Bong and Skaalvik's^[8] academic versus self-regulatory efficacy framework. The ability items target perceived capability to comprehend and master academic content; the action items target perceived capability to carry out specific learning strategies. We started with a pool of 12 items. Two faculty members in educational psychology reviewed them for content appropriateness, clarity, and theoretical alignment, and we kept six (three per dimension). The engagement items cover the emotional and behavioral dimensions in Fredricks *et al.*^[5]. The questionnaire was in Chinese, and so was the source scale, so no translation or back-translation was needed. The item codes (SE1–SE9, ENG5–ENG12) mark their position in the original survey.

Ability self-efficacy. Three items measured confidence in academic capability: “I am confident in handling most problems in my coursework” (SE1), “It is relatively easy for me to persist in completing my coursework” (SE2), and “I believe I can achieve good learning outcomes through my coursework” (SE4). Cronbach's alpha was 0.819. SE2 mentions persistence, yet it sits in the ability factor. Bandura^[3] treats self-efficacy as the perceived capability to organize and execute courses of action, which includes sustained effort. On that reading, persistence is a domain where a student judges their own capability, and the belief that one can persist is a capability assessment rather than a behavioral intention. Empirically, SE2 loaded on the ability factor at $\lambda = 0.779$, next to SE1 ($\lambda = 0.810$) and SE4 ($\lambda = 0.736$), and it correlated more with the other ability items ($r = 0.605$) than with the action items ($r = 0.454$). A competitive model comparison (Section

3.2) also favored the two-factor structure over a single-factor alternative.

Action self-efficacy. Three items measured confidence in executing specific learning strategies: “I can identify key points during lectures” (SE6), “I can organize my study time effectively” (SE7), and “I have a set of study methods that suits me” (SE9). Cronbach’s alpha was 0.775.

Learning engagement. We built a brief composite of emotional and behavioral engagement from four items, following Fredricks *et al.* [5]. Items ENG5 (“I am always curious about the course content I am about to learn”) and ENG8 (“I feel happy when interacting with classmates during coursework”) capture emotional engagement—interest, enjoyment, and positive feelings about learning. Items ENG11 (“I can actively express my views in group study discussions”) and ENG12 (“When I have a learning idea, I put it into practice quickly”) capture behavioral engagement—initiative and participation. The measure has no cognitive engagement. With only four items and no cognitive indicators, we treated them as a single composite instead of separate dimensions; Section 3.2 reports the empirical support for this choice. Cronbach’s alpha was 0.807.

2.3. Analytical strategy

The analysis followed a sequential strategy. First, confirmatory factor analysis (CFA) validated the three-factor measurement model. Second, structural equation modeling (SEM) estimated the structural paths from the two self-efficacy dimensions to learning engagement simultaneously, allowing a direct comparison of their predictive weights. Third, a supplementary composite-score path analysis evaluated the sensitivity of the structural results to the treatment of measurement error. CFA and SEM were conducted in R using the lavaan package [11]. The difference between the two standardized structural coefficients was tested with a Wald test.

CFA was estimated using maximum likelihood (ML), treating the five-category Likert items as approximately continuous. The full-sample item distributions did not show severe nonnormality ($|\text{skewness}| \leq 0.56$, $|\text{kurtosis}| \leq 0.63$). Previous simulation research suggests that five-category items may be treated as approximately continuous under conditions of adequate category use and limited nonnormality [12]. Nevertheless, robust maximum likelihood estimation would provide a more conservative alternative; because robust estimation was not used in the present analysis, this issue is acknowledged as a methodological limitation. Model fit was evaluated using the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and goodness-of-fit index (GFI). Values of CFI and TLI ≥ 0.90 , RMSEA ≤ 0.08 , and GFI ≥ 0.90 were considered acceptable, with GFI ≥ 0.85 as a lenient threshold given the known sensitivity of GFI to model complexity [13,14]. Factor loadings ≥ 0.70 , composite reliability (CR) ≥ 0.70 , and average variance extracted (AVE) ≥ 0.50 were used as thresholds for convergent validity [15–17]. Composite reliability was computed using the formula proposed by Fornell and Larcker [16], and AVE was computed following the procedure described by Hair *et al.* [17]. Discriminant validity was assessed using chi-square difference tests, in which the correlation between each pair of latent factors was constrained to 1, and the resulting decrement in model fit was evaluated [18]. The Fornell-Larcker criterion [16] was also reported as a descriptive reference, although it is known to be overly conservative when latent correlations are high [19]. Both observed composite score correlations (attenuated by measurement error) and latent factor correlations (disattenuated) are reported to provide a complete picture of interconstruct relationships.

Common method bias (CMB) was assessed using two complementary procedures. First, a single-factor model was compared with the three-factor model; a poor-fitting single-factor model suggests that a single common factor does not adequately account for the covariance among the indicators [20,21]. Second,

Harman's single-factor test was conducted to examine the variance explained by the first unrotated principal component. These procedures were interpreted as screening tools rather than definitive tests of CMB^[22].

A supplementary composite-score path analysis was conducted to evaluate the sensitivity of the structural results to the treatment of measurement error. In this analysis, composite scores (item averages) were used as observed variables in place of latent factors, and the structural model was estimated using ordinary least squares regression in the full sample. This approach, which does not model measurement error, has been shown to produce biased parameter estimates when predictors are highly correlated^[23,24]. The comparison between the latent-variable SEM (primary analysis) and the composite-score analysis (supplementary alternative specification) illustrates the sensitivity of the structural conclusions to analytical approach.

3. Results

3.1. Descriptive statistics and correlations

Table 1 presents the descriptive statistics and Pearson correlations among the three factors. All skewness values fell within ± 0.50 and kurtosis within ± 1.00 , indicating no severe departures from normality. The 95% confidence intervals for means indicated that all three constructs scored above the scale midpoint (3.0). The two self-efficacy dimensions were moderately correlated ($r = 0.65$, $P < 0.001$), and both correlated with engagement at similar magnitudes ($r_s = 0.69$ and 0.60 , $P < 0.001$).

Table 1. Descriptive statistics and correlations among study variables ($n = 338$)

Variable	M	95% CI [M]	SD	Skew	Kurt	α	1	2
1. Ability SE	3.51	[3.42, 3.60]	0.86	-0.32	-0.26	0.819	—	
2. Action SE	3.77	[3.68, 3.85]	0.79	-0.20	-0.65	0.775	0.645**	—
3. Engagement	3.59	[3.50, 3.67]	0.81	-0.46	-0.21	0.807	0.689**	0.598**

SE = self-efficacy. CI = confidence interval for the mean based on the t distribution. Correlations are based on observed composite scores (item averages) and are attenuated by measurement error; latent factor correlations from CFA are reported in **Table 3**. ** $P < 0.01$.

3.2. Measurement model

The three-factor CFA fit the data well: $\chi^2(32) = 53.667$, $P = 0.010$, CFI = 0.985, TLI = 0.980, RMSEA = 0.045, 90% CI [0.022, 0.065], GFI = 0.988, SRMR = 0.030. Standardized loadings ranged from 0.670 to 0.810 (**Table 2**). Most were above 0.70; three items (ENG11 = 0.670, SE9 = 0.689, ENG5 = 0.694) fell just short. Loadings above .60 pass when composite reliability and AVE meet their thresholds and the model fits^[15]. Composite reliability ran from 0.773 to 0.819, and AVE from 0.512 to 0.602, which supports convergent validity.

Table 1 reports the observed composite-score correlations, which run from 0.598 to 0.690. Measurement error attenuates these correlations, so they understate the true associations. The CFA latent correlations correct for that error and are correspondingly higher: $r = 0.823$ between ability and action self-efficacy, $r = 0.848$ between ability self-efficacy and engagement, and $r = 0.761$ between action self-efficacy and engagement.

For discriminant validity, we ran chi-square difference tests. We fixed each pair of factors to a correlation of 1 and checked how far the fit fell ^[18]. Fixing any pair at 1 made the fit significantly worse—ability vs. action, $\Delta\chi^2(1) = 46.26$, $P < 0.001$; ability vs. engagement, $\Delta\chi^2(1) = 35.19$, $P < 0.001$; action vs. engagement, $\Delta\chi^2(1) = 64.93$, $P < 0.001$ —so the three constructs are empirically distinct. The Fornell-Larcker criterion, reported for reference, was not met: the latent correlations (0.761–0.848) exceeded the square root of AVE for every pair (0.716–0.776). That criterion is overly conservative when latent correlations are high ^[19], so it does not override the chi-square tests. The high correlations are expected—self-efficacy dimensions overlap by design, and both drive engagement through shared motivational routes—but they also mean the three constructs are not sharply separated. We return to this point in the Discussion.

Table 2. Standardized factor loadings, reliability, and validity indices

Factor	Item	Loading	α	CR	AVE
Ability SE	SE1	0.810	0.819	0.819	0.602
	SE2	0.779			
	SE4	0.736			
Action SE	SE6	0.728	0.775	0.773	0.532
	SE7	0.769			
	SE9	0.689			
Engagement	ENG5	0.694	0.807	0.807	0.512
	ENG8	0.743			
	ENG11	0.670			
	ENG12	0.752			

Table 3. Discriminant validity matrix ($n = 338$)

Construct	1	2	3
1. Ability SE	0.776	46.26	35.19
2. Action SE	0.823	0.729	64.93
3. Engagement	0.848	0.761	0.716

Diagonal (bold) = square root of AVE. Below diagonal = latent factor correlations from CFA. Above diagonal = chi-square difference test statistics ($\Delta\chi^2$, $df = 1$, all $P < 0.001$) for discriminant validity.

Competitive model comparison. To test whether the two-factor self-efficacy structure (ability vs. action) outperformed simpler alternatives, we compared three measurement models on the six self-efficacy items: (a) a single factor with all six items loading on one general self-efficacy factor, (b) two correlated factors for ability and action, and (c) a second-order model with a general factor over the two first-order factors.

The single-factor model fit poorly, $\chi^2(9) = 56.49$, $P < 0.001$, CFI = 0.942, TLI = 0.903, RMSEA = 0.125, so the six items do not reduce to one factor. The two-factor model fit well, $\chi^2(8) = 15.258$, $P = 0.054$, CFI = 0.991, TLI = 0.983, RMSEA = 0.052. The difference was significant, $\Delta\chi^2(1) = 41.23$, $P < 0.001$, $\Delta\text{CFI} = 0.050$. In the two-factor model, ability and action self-efficacy correlated at $r = 0.823$, matching the full three-factor CFA.

At the item level, the average within-dimension correlation ($r = 0.601$ for ability items; $r = 0.536$ for

action items) exceeded the average between-dimension correlation ($r = 0.458$). Items again clustered by their hypothesized factors.

We also ran this comparison in the full structural model with engagement. The three-factor model (SE_Ability, SE_Action, ENG; CFI = 0.985, RMSEA = 0.045) fit better than a two-factor model that folds all self-efficacy items into one factor next to engagement (CFI = 0.957, RMSEA = 0.075), $\Delta\chi^2(2) = 44.57$, $P < 0.001$, $\Delta\text{CFI} = 0.028$. The two self-efficacy dimensions are empirically distinct.

We ran the same check on the four engagement items to see whether emotional and behavioral engagement needed separate factors. A single factor fit excellently, $\chi^2(2) = 0.601$, $P = 0.740$, CFI = 1.000, RMSEA = 0.000. Two factors (emotional vs. behavioral) did not fit better, $\Delta\chi^2(1) = 0.52$, $P = 0.471$, and both AIC (3469.45 vs. 3470.93) and BIC (3500.04 vs. 3505.34) favored one factor. At the item level, the average within-dimension correlation ($r = 0.505$ for emotional; $r = 0.495$ for behavioral) nearly equaled the average between-dimension correlation ($r = 0.517$), so the emotional and behavioral items did not split into clusters. In the full model, splitting engagement into two factors (a four-factor model) did not improve fit over three factors (CFI = 0.984 vs. 0.985, $\Delta\text{CFI} = -0.002$, $\Delta\chi^2(3) = 0.68$, $P = 0.879$). We therefore treat the four engagement items as one composite. Without cognitive engagement items, this measure cannot capture the full construct, so we call it a brief composite of emotional and behavioral engagement rather than a full engagement measure.

3.3. Common method bias

Because all constructs were measured through self-report at a single time point, common method bias (CMB) was a potential concern. A single-factor model yielded RMSEA = 0.097 and CFI = 0.926, indicating poor fit relative to the three-factor model ($\Delta\text{CFI} = 0.059$). However, a poor-fitting single-factor model does not rule out method variance, as CMB may coexist with the substantive multi-factor structure^[20]. Harman's single-factor test showed that the first unrotated principal component explained 52.2% of variance, slightly exceeding the 50% threshold conventionally regarded as suggestive of potential CMB concern. Harman's test has low diagnostic power and is not considered a definitive test of CMB^[22].

An unmeasured latent method factor model was also considered; however, this model did not yield an admissible and properly identified solution in the present sample, and its unstable parameter estimates were therefore not interpreted or reported. The two checks together point to some method variance, but no single common factor accounts for the covariance among the indicators or erases the distinction among the three constructs.

3.4. Structural model

The structural model specified engagement as a latent outcome predicted simultaneously by ability and action self-efficacy, with the measurement model and structural paths estimated jointly in R lavaan (**Table 4**). In the full sample, ability self-efficacy was a significant predictor of engagement ($b = 0.594$, $SE = 0.110$, $\beta = 0.685$, 95% CI [0.379, 0.808], $P < 0.001$), while action self-efficacy was not ($b = 0.211$, $SE = 0.127$, $\beta = 0.197$, 95% CI [-0.038, 0.461], $P = 0.097$). The full-sample model explained 73.1% of the variance in engagement ($R^2 = 0.731$). A Wald test comparing the two coefficients was significant on the unstandardized scale ($z = 6.71$, $P < 0.001$) but only marginally significant on the standardized scale ($z = 2.03$, $P = 0.043$). Thus, H1 received directional support: ability self-efficacy showed a larger coefficient than action self-efficacy, although the standardized difference reached only marginal significance.

Table 4. Unstandardized and standardized path coefficients from self-efficacy to engagement ($n = 338$)

Parameter	Full sample ($n = 338$)
Ability SE $\rightarrow$ ENG: b (SE)	0.594*** (0.110)
Ability SE $\rightarrow$ ENG: 95% CI	[0.379, 0.808]
Ability SE $\rightarrow$ ENG: β	0.685
Ability SE $\rightarrow$ ENG: P	< .001
Action SE $\rightarrow$ ENG: b (SE)	0.211 (.127)
Action SE $\rightarrow$ ENG: 95% CI	[-0.038, 0.461]
Action SE $\rightarrow$ ENG: β	0.197
Action SE $\rightarrow$ ENG: P	0.097
R^2 (ENG)	0.731

b = unstandardized coefficient; SE = standard error; β = standardized coefficient; CI = confidence interval for the unstandardized coefficient. The structural model showed acceptable fit: $\chi^2(32) = 53.667$, CFI = 0.985, TLI = 0.980, RMSEA = 0.045, SRMR = 0.030. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

3.5. Sensitivity analysis: Composite-score path analysis

To see whether the structural results depend on how we handle measurement error, we added a composite-score path analysis. Composite scores (item averages) substitute for latent factors, and the structural model is estimated with ordinary least squares on the full sample. Unlike latent-variable SEM, this approach ignores measurement error and can bias the estimates when predictors are highly correlated^[23,24].

The composite-score analysis again yielded the larger estimate for ability self-efficacy. In the full sample, both paths were significant: ability self-efficacy ($b = 0.489$, $SE = 0.046$, $\beta = 0.519$, $P < 0.001$) and action self-efficacy ($b = 0.268$, $SE = 0.050$, $\beta = 0.264$, $P < 0.001$). R^2 was 0.515, well below the 0.731 from the latent-variable SEM, because the composite scores carry measurement error. So ability self-efficacy kept the larger estimate in both specifications, even though the significance of action self-efficacy shifted.

Methodological work points the same way, so we keep the latent-variable SEM as the primary analysis^[23]. Its higher R^2 (0.731 vs. 0.515) partly reflects that modeling measurement error removes attenuation, but the two R^2 values cannot be read as an accuracy test—the dependent variable is scaled differently in the two approaches. We report the composite-score results as a supplementary alternative specification. Ability self-efficacy kept the larger estimate either way.

4. Discussion

4.1. Differential predictive weight of ability and action self-efficacy

The main result is that ability self-efficacy carried the larger coefficient, though the two coefficients differed only marginally (Wald $z = 2.03$, $P = 0.043$). In the full-sample model, ability self-efficacy predicted engagement ($b = 0.594$, $\beta = 0.685$, 95% CI [0.379, 0.808], $P < 0.001$); action self-efficacy did not ($b = 0.211$, $\beta = 0.197$, 95% CI [-0.038, 0.461], $P = 0.097$). The model explained 73.1% of the variance in engagement. This fits the ability–action distinction from social cognitive theory: confidence in academic capability emerges as the more proximal driver of engagement than confidence in executing study strategies. Bong and Skaalvik^[8] noted that an efficacy dimension’s functional weight can vary across learners, and academic self-efficacy is among the strongest motivational correlates of engagement^[4].

At the composite-score level, ability and action self-efficacy correlated at $r = 0.645$ ($VIF = 1.72$), so severe multicollinearity was not present in the observed scores. This does not rule out instability in the latent-variable SEM, where the two predictors were estimated together with the measurement model and correlated highly. A difference between significant and non-significant is itself not necessarily significant^[25], which fits our comparison of the two dimensions.

4.2. Sensitivity of the action self-efficacy estimate

The comparison between the latent-variable SEM and the composite-score analysis converged on the larger point estimate for ability self-efficacy but yielded different significance patterns for action self-efficacy. In the latent-variable model, the full-sample standardized coefficients were $\beta_{\text{Ability}} = 0.685$ and $\beta_{\text{Action}} = 0.197$; in the composite-score model, the corresponding coefficients were $\beta_{\text{Ability}} = 0.519$ and $\beta_{\text{Action}} = 0.264$. This sensitivity is notable given the high correlation between the two self-efficacy dimensions ($r = 0.823$), which creates conditions under which composite-score and latent-variable methods can diverge^[23]. The latent-variable approach is preferred based on methodological recommendations^[23,24], though the higher R^2 in the latent-variable model (0.731 vs. 0.515) should not be interpreted as a direct accuracy comparison because the two approaches scale the dependent variable differently.

4.3. Implications and limitations

Ability self-efficacy carried the larger estimate in both specifications, so capability beliefs are a plausible target for future experiments. Confidence in academic capability was more strongly tied to engagement than confidence in executing strategies, so interventions that build foundational capability beliefs—through mastery experiences and achievable early successes, for example—may deserve priority over strategy-focused training in this population. Such studies could compare capability-focused and strategy-focused support, but they would not settle which to prioritize, and the cross-sectional design rules out causal claims about intervention outcomes.

Several limitations should be noted. First, the cross-sectional design precludes causal inference; the structural model specified self-efficacy as a predictor of engagement based on theory, but reverse causation or reciprocal effects are plausible, and longitudinal designs or cross-lagged panel models are needed to establish directional effects. Second, all constructs were measured through self-report at a single time point, and common method variance may have inflated the observed associations; although the single-factor model fit poorly and Harman's test was only marginally suggestive, method effects cannot be fully ruled out. Third, the engagement measure was a brief four-item composite of emotional and behavioral engagement without cognitive engagement, and the self-efficacy measures were brief three-item scales adapted from a single source; more comprehensive, validated measures would strengthen the conclusions. Finally, the sample was drawn from a single university and a single cohort of top-up degree students, which limits generalizability.

5. Conclusion

This study examined the differential associations of ability and action self-efficacy with learning engagement among Chinese top-up degree students. In the structural model, ability self-efficacy showed a significant positive association with engagement ($\beta = 0.685$, $P < 0.001$), whereas action self-efficacy did not reach significance ($\beta = 0.197$, $P = 0.097$), and the model explained 73.1% of the variance in engagement.

The larger point estimate for ability self-efficacy was robust across latent-variable and composite-score specifications, although the statistical significance of action self-efficacy was sensitive to the analytical approach. These findings suggest that, among top-up degree students, confidence in one's academic capability may be a more proximal predictor of engagement than confidence in executing learning strategies, although the standardized difference between the two dimensions reached only marginal significance. The results should be interpreted as exploratory given the cross-sectional design, the self-report measurement, and the high correlation between the two self-efficacy dimensions. Future studies should use validated and more comprehensive measures, longitudinal or experimental designs, and multiple data sources to strengthen causal and discriminant conclusions.

Funding

This work was supported by the Beijing Union University Graduate School-Level Educational Science Research Project (2025) under Grant No. YK202506.

Disclosure statement

The authors declare no conflict of interest.

Author Contributions

Xinyu Hu: Conceptualization, methodology, questionnaire development, data collection, formal analysis, and original draft preparation.

Wei Li: Supervision, methodological review, development, data collection, interpretation of findings, manuscript revision, and project administration.

Both authors approved the final manuscript and agree to be accountable for all aspects of the work.

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