**Online Supplementary Materials**

**Longitudinal Associations between Academic Competence-Building and Depression Symptoms**

**in Early Adolescence**

Table S1

*Competence-Building Qualities Assessed in the Current Research*

|  |  |  |
| --- | --- | --- |
| Construct | Definition | Example item |
| Academic self-control (Park et al., 2017; Tsukayama et al., 2013) | The tendency to align one’s academic behaviors with standards and goals. | I did my homework right away, instead of waiting until the last minute. |
| Grit (Duckworth & Quinn, 2009)  | The tendency to sustain effort over the long term. | I keep working hard even when I feel like quitting. |
| Mastery orientation (Midgley et al., 2000) | The goal to develop one’s competence in class work. | One of my goals in class is to learn as much as I can. |
| Autonomous motivation (Ryan & Connell, 1989) | The motivation to engage in academic behaviors for reasons related to enjoyment or personal importance. | I enjoy doing my school work well. |
| Academic self-efficacy (Midgley et al., 2000) | The perception of one’s competence to do class work.  | I'm certain I can figure out how to do the most difficult class work. |
| Expectancy (Pintrich et al., 1991) | The expectation that one can attain a desired academic performance outcome. | Considering the difficulty of my subjects, I think I will do well in my exams. |
| Intellectual interest (Pintrich et al., 1991) | The tendency to seek out and engage in opportunities for intellectual engagement. | I prefer work that is challenging so that I can learn new things. |

Table S2

*Longitudinal Measurement Invariance of Latent Constructs at Each Level of Equivalence*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Models | χ2(*df*) | *p* | TLI | CFI | RMSEA | 95% CI | SRMR |
| Academic competence-building |  |  |  |  |  |  |  |
| T1 measurement model | 44.38 (14) | < .001 | .981 | .988 | .054 | [.037 - .072] | .057 |
| T2 measurement model | 26.03 (14) | .026 | .993 | .995 | .034 | [.012 - .054] | .044 |
| T3 measurement model | 15.57 (14) | .341 | .999 | .999 | .012 | [.000 - .039] | .034 |
| Configural (varying λ, μ, ε) | 85.97 (42) | < .001 | .991 | .994 | .038 | [.026 - .049] | .041 |
| Metric (equal λ, varying μ, ε) | 101.61 (54) | < .001 | .993 | .994 | .035 | [.024 - .045] | .044 |
| Scalar (equal λ, μ, varying ε) | 124.72 (66) | < .001 | .993 | .992 | .035 | [.025 - .044] | .048 |
| Strict (equal λ, μ, ε) | 157.18 (80) | < .001 | .992 | .990 | .036 | [.028 - .044] | .059 |
|  |  |  |  |  |  |  |  |
| Depression symptoms  |  |  |  |  |  |  |  |
| T1 measurement model | 43.23 (35) | .160 | .993 | .994 | .018 | [.000 - .034] | .051 |
| T2 measurement model | 21.68 (35) | .962 | 1.000 | 1.000 | .000 | [.000 - .000] | .035 |
| T3 measurement model | 38.53 (35) | .313 | .997 | .998 | .012 | [.000 - .030] | .048 |
| Configural (varying λ, μ, ε) | 103.43 (105) | .525 | 1.000 | 1.000 | .000 | [.000 - .018] | .041 |
| Metric (equal λ, varying μ, ε) | 118.25 (123) | .605 | 1.000 | 1.000 | .000 | [.000 - .016] | .044 |
| Scalar (equal λ, μ, varying ε) | 145.14 (141) | .388 | .999 | .999 | .006 | [.000 - .019] | .046 |
| Strict (equal λ, μ, ε) | 171.94 (161) | .263 | .998 | .998 | .010 | [.000 - .020] | .054 |

 *Note.* λ = factor loadings; μ = item intercepts; ε = item error variances; TLI = Tucker-Lewis index; CFI = confirmatory fit index; RMSEA = root mean square error of approximation with 95% confidence interval; SRMR = square root mean residual.

Table S3

*Change in Fit Indices for Different Levels of Longitudinal Measurement Invariance Models*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Δχ2(*df*) for comparison | *p* | ΔCFI | ΔRMSEA | ΔSRMR |
| Academic competence-building |  |  |  |  |  |
| Metric versus configural invariance  | 15.63 (12) | .208 | -.001 | -.003 | .004 |
| Scalar versus metric invariance | 34.51 (12) | < .001 | -.001 | .000 | .003 |
| Strict versus scalar invariance | 39.74 (14) | < .001 | -.002 | .001 | .011 |
|  |  |  |  |  |  |
| Depression symptoms  |  |  |  |  |  |
| Metric versus configural invariance  | 11.76 (18) | .859 | .000 | .000 | .003 |
| Scalar versus metric invariance | 34.14 (18) | .012 | -.001 | .006 | .002 |
| Strict versus scalar invariance | 30.99 (20) | .055 | -.001 | .003 | .008 |

*Note.* Δ = change in specific parameter estimate; CFI = confirmatory fit index; RMSEA = root mean square error of approximation; SRMR = square root mean residual. From the unconstrained model to constrained model, ∆CFI values of ≤ -.010, ∆RMSEA values of ≤ .015, and ∆SRMR of ≤ .030 implies invariance of the constrained model (see Chen, 2007; Cheung & Rensvold, 2002).

Table S4

*Factor Loadings of Academic Competence-Building and Depression Symptoms*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Estimate | *SE* | T1 std loadings | T2 std loadings | T3 std loadings |
| Acad competence-building |  |  |  |  |  |
| Acad self-control | 1.000 |  | .615 | .675 | .657 |
| Grit | 1.153 | .039 | .722 | .775 | .759 |
| Mastery goal | 1.047 | .039 | .707 | .761 | .745 |
| Auto motivation | 0.934 | .031 | .675 | .732 | .716 |
| Acad self-efficacy | 1.168 | .042 | .716 | .769 | .754 |
| Expectancy | 1.025 | .043 | .606 | .667 | .649 |
| Intel curiosity | 1.169 | .042 | .701 | .756 | .740 |
|  |  |  |  |  |  |
| Dep symptoms |  |  |  |  |  |
| RCADS1 | 1.000 |  | .635 | .679 | .646 |
| RCADS4 | 0.849 | .048 | .542 | .587 | .552 |
| RCADS8 | 0.908 | .054 | .496 | .541 | .507 |
| RCADS10 | 0.695 | .048 | .485 | .530 | .496 |
| RCADS13 | 0.834 | .049 | .618 | .663 | .629 |
| RCADS15 | 0.825 | .046 | .619 | .664 | .630 |
| RCADS16 | 1.023 | .046 | .643 | .687 | .653 |
| RCADS19 | 0.940 | .054 | .559 | .605 | .570 |
| RCADS21 | 1.167 | .055 | .577 | .622 | .588 |
| RCADS24 | 0.936 | .054 | .542 | .587 | .552 |

*Note*. Factor loadings from the strict measurement invariance models are presented. All loadings are significant at *p* < .001.

std loadings = standardized loadings.

.70\*\*\*

[.67, .03]

.72\*\*\*

[.81, .04]

Competence-Building

T3

Competence-Building

T2

Competence-Building

T1

-.07\*

[-.09, .04]

-.05

[-.08, .06]

-.09\*

[-.01, .00]

-.16\*\*\*

[-.02, .01]

-.30\*\*\*

[-.06, .01]

-.06

[-.04, .02]

-.05

[-.03, .02]

.66\*\*\*

[.61, .04]

Depression Symptoms T1

Depression Symptoms T3

Depression Symptoms T2

.68\*\*\*

[.74, .04]

Figure S1. CLPM for academic competence-building and depression symptoms. Standardized estimates (unstandardized estimates and standard errors in brackets) are presented. Solid lines denote significant parameters; dashed lines denote nonsignificant parameters. Gender and SES were specified as covariates but they are not shown here for presentation clarity.

\* *p* < .05. \*\*\* *p* < .001.

**Appendix**

**Notes on the CLPM**

Like in the RI-CLPM analysis, we tested the possibility that the autoregressive and cross-lagged paths were equal across time points (i.e., T1-T2, T2-T3) in the corresponding CLPM. The chi-square difference test was significant, Δχ2(4) = 14.985, *p* = .005. Hence, the complex model with freely estimated autoregressive and cross-lagged paths was preferred. This CLPM between academic competence-building and depression symptoms is depicted in Figure S1. As expected, the autoregressive stability coefficients were strong and significant for both variables. More critically, all cross-lagged paths were not significant, with the exception of the T2-T3 cross-lagged path from depression to competence-building (β = -.07, *p* < .05). Overall, there is little evidence to suggest the presence of mutual and reciprocal longitudinal associations between academic competence-building and depression symptoms.

The differences in results obtained from RI-CLPM versus CLPM merit some discussion. The RI-CLPM yielded significant cross-lagged effects from academic competence-building to subsequent depression, but nonsignificant effects from depression to subsequent competence-building. However, the corresponding CLPM yielded nonsignificant cross-lagged paths between the two constructs, consistent with some prior work (e.g., Defoe et al., 2013; Vaillancourt et al., 2013). Differences in the cross-lagged effects across the RI-CLPM and CLPM were not entirely unexpected as they addressed different questions (see Orth et al., 2021). The question being addressed by the RI-CLPM cross-lagged effects was whether adolescents who had lower competence-building than usual would experience a subsequent increment in depression (and vice-versa). The question being addressed by the CLPM cross-lagged effects was whether adolescents who had lower competence-building (relative to others) would experience a subsequent rank-order increase in depression (and vice-versa).

**Power Analysis**

 As the RI-CLPM was relatively new, few simulation studies had been conducted to ascertain the minimal sample size required via a power analysis. Masselink et al. (2018) provided an indicative estimate that a 3-wave RI-CLPM might need a minimum sample size of about 1,500 to ensure adequate power to detect small within-individual cross-lagged associations (see their supplementary materials; Appendix A). Barzeva et al. (2020) conducted an a priori power analysis assuming small within-individual cross-lagged effects in their RI-CLPMs and confirmed that their sample size of over 2,700 provided adequate power (> .80) to detect those small cross-lagged effects (see their supplementary materials). What these two studies showed was that the RI-CLPM requires large sample sizes (i.e., more than 1,500) to achieve adequate power to detect small within-individual cross-lagged associations.

 To determine the power associated with our RI-CLPM, we conducted Monte Carlo simulations using M*plus* version 8.0 (Muthén & Muthén, 1988-2017). As there were no prior RI-CLPM studies done concerning our focal variables, we relied on the parameter estimates obtained from our data. Because we had imputed missing data, and had used all data from the 741 adolescents, we conducted the simulations under the condition of no missing data.

The results are presented in Table S5. In the academic competence-building and depression RI-CLPM, our current sample size was able to detect the between-individual association and stability effects at a power .71 and above. For the within-individual cross-lagged associations, the generally small effects yielded low power estimates. For the cross-lagged effects from academic competence-building to depression symptoms, the estimated power estimates were on average around .35. Following prior work (Barzeva et al., 2020; Masselink et al., 2018), we considered that cross-lagged associations needed to be .10 and greater for us to interpret them substantively. As the cross-lagged associations from depression symptoms to academic competence-building were less than .10 in magnitude, we considered these associations to be likely trivial.

In summary, with our sample size of 741, the power associated with the cross-lagged paths in the RI-CLPM associated with academic competence-building and depression symptoms was on average about .35. We conducted further Monte Carlo simulations and found that we needed a sample size of 1,600 to achieve a power of greater than .80 for the T2-T3 cross-lagged path (β = -.13). This estimate was consistent with the simulation results obtained in Masselink et al. (2018), supporting the proposal that a 3-wave RI-CLPM would likely require a minimal sample size of 1,500 to achieve a power of .80 for small cross-lagged associations. By most accounts, our sample size of 741 would be considered large, and we had obtained this size despite practical and resource challenges. The RI-CLPM, though requiring extremely large sample sizes, confers the distinct advantage of parsing apart between- and within-person sources of variance. While acknowledging that the significant within-person cross-lagged effects obtained in the current analyses had only about 35% power, we believed that they represented substantive associations that warrant our attention. We recommend that future RI-CLPM analysis using the same variables here strive to obtain power estimates before the designing the study. Finally, we caution that the power estimates obtained here may not generalize to other studies because they are dependent on several factors, including the number of measurement occasions, the size of the effects, variance distributions, and the extent of missing data.

Table S5

*Power Analyses for RI-CLPM without Missing Data*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Parameter | Observed effect | Power |
| Betw-individual | Acad – Dep | -.31 | .85 |
| Stability  | T1 Acad – T2 Acad | .37 | .96 |
|  | T2 Acad – T3 Acad | .46 | 1.00 |
|  | T1 Dep – T2 Dep | .22 | .71 |
|  | T2 Dep – T3 Dep | .28 | .94 |
| Cross-lagged  | T1 Acad – T2 Dep | -.09 | .22 |
|  | T2 Acad – T3 Dep | -.13 | .47 |
|  | T1 Dep – T2 Acad | -.07 | .18 |
|  | T2 Dep – T3 Acad | -.08 | .31 |
| Within-time | T1 Acad – T1 Dep | -.29 | .95 |
|  | T2 Acad – T2 Dep | -.19 | .84 |
|  | T3 Acad – T3 Dep | -.11 | .76 |

*Note*. Monte Carlo simulation done based on a sample size of 741, with missing data imputed. Acad = academic competence-building; Dep = depression symptoms.

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