Thought Question: Why does student agency require intentional development during the middle school years leading up to the transition to high school?

Research Article: Student Agency at the Crux: Mitigating Disengagement in Middle and High School

Subject Area: Student Agency

Authors: Anderson, R., Graham, M., Kennedy, P., Nelson, N., Stoolmiller, S. . Baker, S., & Fien, H.
Date: 2019

Abstract
This study examines how two primary factors of personal agency, self-efficacy and perceived control, are relevant in the decline of student engagement between middle school and high school. A key finding is the importance of middle school in determining a student's educational pathway. Study results indicate that the resilience factor of self-efficacy was a key determiner in student disengagement, and that when self-efficacy drops, disengagement increases between the end of middle school and transitioning into high school. Self-efficacy cultivated during middle school plays a key role in student high school engagement and performance. The study findings suggest that it would be beneficial for schools to consider programs that develop personal student agency during middle school and in the transitional high school years.

Keywords: Self-efficacy; engagement; disengagement; middle school transition to high school; student agency; resiliency;

Enjoy the article! **And remember…** developing student self-efficacy in learning during middle school can support student engagement and performance throughout their middle and high school years.

Contemporary Educational Psychology 56 (2019) 205–217

Contents lists available at ScienceDirect

Contemporary Educational Psychology

journal homepage: www.elsevier.com/locate/cedpsych

Student agency at the crux: Mitigating disengagement in middle and high school

Ross C. Anderson[a,*], Matthew Graham[a], Patrick Kennedy[b], Nancy Nelson[b], Michael Stoolmiller[b], Scott K. Baker[c], Hank Fien[b]

[a] Inflexion, 1700 Millrace, Eugene, OR 97403, United States
[b] The Center on Teaching and Learning at the University of Oregon, 1600 Millrace, Suite 207, Eugene, OR, 97403, United States
[c] Faculty at Southern Methodist University, Dallas, TX, United States

ARTICLE INFO

Keywords:
Agency
Self-efficacy
Engagement
Latent growth curve analysis
Dual change score model

ABSTRACT

Considerable evidence indicates that students' academic motivation and engagement generally decline as they move through middle school and on to high school. This study applied social cognitive theory to explore how self-efficacy and perceived control—two main factors of personal agency—may play a role in mitigating this decline in engagement and further contribute to academic performance. We used dual change score modeling to examine the dynamic structure of personal agency and disengagement during grades 8–10 for a large sample of students from the Pacific Northwest in the U.S. In that model, we analyzed how those variables predicted grade point average and attendance for students at the end of 10th grade. Students did not necessarily become more disengaged as a result of lower perceptions of control, rather they became more disengaged without the resilience factor of self-efficacy. The actual influence of disengagement on attendance and academic performance appears to be far weaker than the role of personal agency factors. Our results indicate that when student's self-efficacy drops, disengagement in school increases during the years transitioning to high school. Increased disengagement weakens perceived control and change in both the control and self-efficacy dimensions of personal agency drive academic performance. Schools should prioritize the development of personal agency in each student during the middle school to high school transition years.

1. Introduction

Since the inception of engagement as a construct of interest (Finn, 1989; Mosher & MacGowan, 1985), researchers have documented how facets of engagement in the classroom contribute to student success in school (Eccles, 2016; Finn & Owings, 2006; Klem & Connell, 2004). Regrettably, considerable evidence indicates that students' academic motivation and engagement generally decline as they move through middle school and on to high school (Eccles & Roeser, 2011; Fredricks & Eccles, 2002; Wigfield, Byrnes, & Eccles, 2006). Moreover, research indicates that declines in motivation and engagement in school during the middle grades predict later high school dropout or failure (Finn, 2006; Roeser & Eccles, 1998). In response to these findings, researchers have given considerable attention to understanding the reasons for these declines, such as the potential mismatch between typical middle and high school environments and the developmental needs of adolescent learners (Eccles & Roeser, 2011). Reforms for middle school have sought to improve school climate among other factors (Juvonen, Le, Kaganoff, Augustine, & Constant, 2004; West & Schwerdt, 2012); yet, the problem persists. The middle years still matter and continued effort is warranted to understand what factors protect from the trend of declining motivation and engagement in school.

Extensive research has led to the field's understanding of motivation and engagement in school to be a mix of distinct behavioral, affective, and cognitive factors (Eccles, 2016; Fredericks, Blumenfeld, & Paris, 2004). Poor affective engagement in school contributes to decreased behavioral engagement through weaker attendance and participation and the danger of dropping out (Appleton, Christenson, Kim, & Reschly, 2006). Still, changes in motivation and engagement factors during middle and high school, and how they relate to one another, remains unclear due to sparse longitudinal research (Wang & Eccles, 2012; You & Sharkey, 2009). For instance, research on the relation of various engagement factors has looked at different profiles of change over time (Janosz, Archambault, Morizot, & Pagani, 2008; Wylie & Hodgen, 2012) and cross-sectional differences in student cohorts at different grade levels (Johnson, Crosnoe, & Elder, 2001; Marks, 2000). Yet, the

* Corresponding author at: Inflexion, 1700 Millrace, Eugene, OR 97405, United States.
E-mail address: ross.anderson@inflexion.org (R.C. Anderson).

https://doi.org/10.1016/j.cedpsych.2018.12.005

Available online 24 January 2019

use of modeling to understand relations between engagement and motivation factors, in addition to their influence on academic performance, remains largely limited to a single year in middle school or high school (Green et al., 2012; Wang & Eccles, 2013). The incorporation of multidimensional theories and longitudinal analyses is needed to conceptualize and test comprehensive models that can better inform theory and practice. Social cognitive theory (SCT; Bandura, 1986, 2006) provides one theoretical perspective that identifies multiple motivational factors and processes critical to students' engagement and academic performance in school. As such, Bandura's conceptualization of personal agency guides this investigation.

1.1. Disengagement: developmental, environmental fit, or both?

Though a body of work covering the past three decades has explored different conceptualizations and dimensions of engagement (e.g., Mosher & MacGowan, 1985; Appleton et al., 2006; Christenson, Reschly, & Wylie, 2012; Eccles, 2016; Fredericks et al., 2004), few studies analyzed developmental trajectories (Gottfried, Fleming, & Gottfried, 2001; Janosz et al., 2008; Johnson et al., 2001; Marks, 2000; Wang & Eccles, 2012; You & Sharkey, 2009). In general, those studies documented a downward trajectory as students' age through the K-12 system. Nearly three decades ago Eccles and Midgley (1989) suggested that the downward trend of disengagement may be due to poor stage-environment fit from a developmental perspective, indicating that the middle school model (Grades 6–8) may be developmentally harmful in early adolescence. Juvonen et al. documented a number of features of the typical middle school model that likely have a negative effect on adolescent development and noted that "the creation of separate schools for young adolescents has been guided primarily by pragmatic concerns" rather than concerns of developmental needs (2004; p. 18). Those misaligned features include (a) a focus on academic competition in place of individual development, (b) the demands of school transition during the difficult onset of puberty, (c) inflexible scheduling with many classroom changes, (d) a lack of interdisciplinary learning, (e) distant relationships with teachers, and (f) increased between-class ability grouping, among others. Little has changed since those observations (see Eccles & Roeser, 2011; West & Schwerdt, 2012). In this light, transitions in K-12 education from elementary to middle and middle to high school are not the cause of the declines (Roeser & Eccles, 1998); rather the nature of the environments which students transition through may explain the uptick in disengagement.

As past research indicates (Balfanz, Herzog, & Mac Iver, 2007), middle school academic experiences and patterns of engagement are highly predictive of high school engagement, persistence, and eventual successful completion. Self-system theory supports the stability of these patterns of disengagement, suggesting that the environment shapes the experience of an individual. That conditioning influences and reinforces an individual's self-efficacy in that setting, for instance (Skinner, Furrer, Marchand, & Kinderman, 2008). Therefore, the conditions of the educational setting would need to change substantially to shift an individual's level of engagement. However, the intensity of academic competition in typical high school settings may be too similar to typical middle school to disrupt negative patterns in that stage of schooling (Juvonen et al., 2004). For instance, academic tracking that separates students based on ability often begins in middle school. Assuming a degree of homogeneity of educational setting, it is possible that factors of personal agency may play a pivotal role in disrupting the trend of increasing disengagement from middle to high school.

To extend understanding about how and why student engagement changes during adolescence, the field needs more conceptual and theoretical clarity about the dynamic interplay between motivational factors of agency and school engagement (Eccles, 2016; Green et al., 2012). Because components of engagement and motivation overlap considerably in research, clarity about directionality of influence between factors over time has been a challenge. Nevertheless, across frameworks, it appears that "motivation underpins factors of engagement and that engagement leads to outcomes such as achievement" (Martin, 2012, p. 305). SCT provides a theoretical lens to specify how certain motivation factors related to personal agency may disrupt the trend of disengagement in middle and high school and contribute to academic performance.

1.2. Social cognitive theory: personal agency as resilience factor

SCT has been applied recently to understand student agency as a resilience factor (Burger & Walk, 2016; Martin, Burns, & Collie, 2017). SCT proposes that "to be an agent is to influence intentionally one's functioning and life circumstances" (Bandura, 2006, p. 164). Bandura's conceptualization stresses the ideas of (a) *influence*, including the perceived control over one's actions and outcomes, and (b) *intentionality*, including the self-efficacy to feel capable of directing one's actions and dictating the outcomes. SCT promotes the individual as a proactive agent in a social environment. As such, SCT makes a distinction between three modes of agency—personal, proxy, and collective. In this study, we focus on the foundations of personal agency, where the individual can influence their own choices and actions and the events around them through belief of personal efficacy and perceived control over performance outcomes (Bandura, 2006). Self-efficacy and perceived control have received extensive theoretical development on their own and, recently, have been merged together in research to form a foundational composite of personal agency (e.g., Burger & Walk, 2016; Martin et al., 2017).

Self-efficacy posits that individuals who believe in their ability and capacity to perform well, even in the face of challenges, will consider alternative possibilities rather than dwell on deficiencies and barriers (Bandura, 1986, 1997). Low self-efficacy can weaken one's self-confidence to engage, apply effort, and take on challenges that inevitably arise (Zimmerman, 2000). This process can overwhelm other adaptive factors of motivation, such as perceived control, and factors of engagement, such as participation in school (Green et al., 2012). Like other adaptive factors, a students' self-efficacy in their ability to succeed in school can be self-reinforcing and create expectancy for either achievement or failure. Therefore, if general self-efficacy about school is low entering high school, it may be challenging to overcome obstacles and may relate to a decrease in perceived control and increased disengagement.

Although self-efficacy is most often studied at the task- or domain-specific level, scholars have also investigated the role that more general conceptions of self-efficacy can play for individuals. These general applications have aimed to gauge how efficacious students feel about a broad capacity (e.g., academic, social, emotional, etc.) in a broad context, such as school or in the face of challenges across situations in life, more generally. For instance, Martin et al. (2017) operationalized agency by measuring general academic self-efficacy in school rather than in a specific subject (this current study followed Martin's approach). Amitay and Gumpel (2015) used Muris (2001) self-efficacy measure to study general academic self-efficacy, emotional self-efficacy, social self-efficacy, and life-general self-efficacy of adjudicated girls. Burger and Samuel (2017) studied general life self-efficacy, among other generalized forms, as well. Each of those examples contributed to theoretical and practical considerations, framing self-efficacy as a mitigating and protective factor, even when considered in more general terms. Specifically for school leaders, the study of general self-efficacy may be useful in the design of school culture, structures, and systems that support students' overall sense of self-efficacy in their school experience. This general approach to self-efficacy requires researchers and practitioners to expand their view of a students' experience in school and other contexts beyond the isolation of a specific subject area or task. Whereas past research on self-efficacy at the task- or domain-specific levels has clarified its important role in performance, self-efficacy research at the general level may be able to support

greater understanding about its role as a protective factor for broader outcomes, such as high school graduation.

Perceived capacity to control actions and outcomes in an environment has been posited through numerous theories (e.g., Bandura, 2006; Weiner, 1985) to be fundamental to human motivations. Perceived control in learning may entail commitment and effort to seek out resources and courses of action that promote that sense of control. Indeed, Patrick, Skinner, and Connell (1993) found that perceived control predicted adaptive motivations for future behaviors. Through a SCT perspective, self-efficacy is closely related to perceived control and control knowledge in a context, environment, or task and supports self-directed courses of action (Zimmerman, 2000). Following Martin et al. (2017) operationalization, we included perceived control over success or failure in academic performance in its diminished state—*uncertain control*—as part of students' personal agency. Though Bandura (1986) and others have contended that generalized control and self-efficacy perceptions may not meaningfully relate to performance, more research is needed to understand potential contributions to theory and practice from the study of general beliefs and perceptions. For instance, school counseling may benefit from considering the role of general agency in student action and beliefs. Indeed, others (e.g., Burger & Samuel, 2017; Martin et al., 2017) have found general self-efficacy to be a key resilience factor in adolescence. We aim to contribute further understanding about how much self-efficacy and perceived control in school influence engagement and performance.

1.3. Role of agency in academic performance and engagement

Generality of self-efficacy and perceived control refers to transferability across academic activities rather than a specific focus on one task or domain (Zimmerman, 2000). Notably, self-efficacy focuses on prospective performance capabilities rather than on personal qualities in retrospection, such as evaluations of self-esteem or self-concept. Therefore, self-efficacy can serve as a causal agent of motivation, engagement, and academic performance. Especially in middle school (Usher & Pajares, 2006), domain-specific self-efficacy is generated through direct experience and mastery as well as through vicarious experiences and social persuasion. In the school environment, students with general self-efficacy and perceived control about their capacity to be successful in school are more likely to engage in more challenging tasks (Zimmerman, 2000) and experience positive outcomes (Green et al., 2012). For instance, both aspects of personal agency, measured at the general academic level, related to greater achievement for students with attention deficit hyperactivity disorder (Martin et al., 2017). Beyond just academic performance, domain-specific self-efficacy beliefs can even predict the college majors and career paths of students (Hackett, 1995). As a whole, the evidence from decades of research reinforces that these factors of personal agency at both task-specific and generalized levels play instrumental roles in how students engage in and succeed academically in school. More work is needed to understand how factors of general personal agency influence students' affective engagement and interest, behavioral engagement to attend and participate in school, and, ultimately, their performance to meet or surpass academic expectations.

1.4. Change in agency and engagement during adolescence

Engagement in school is important for academic performance and later life outcomes (Martin, 2012); however, Gottfried et al. (2001) found a general decline of engagement from middle elementary to high school years across student groups. Although their study design lacked controls for auto-correlation and may have biased estimates, the decline in engagement was apparent. Importantly, though, not all students experience the same type of decline. Wylie and Hodgen (2012) found that different trajectories of engagement explain differences in school performance—a higher rate of decline linked to lower performance. Using a person-centered modeling approach to understand change in engagement, Janosz et al. (2008) applied growth mixture modeling to derive seven distinct trajectories of engagement from the age of 12 to 16. Three classes showed stable trajectories, two classes showed increasing or decreasing trends, and two classes demonstrated transitory trajectories, which increased and decreased during that time period. Importantly, the researchers found that unstable trajectories significantly predicted dropping out of high school. Those studies modeled change in engagement but leave questions about the change in personal agency and its potential role as a protective factor for engagement. Regarding agency factors, Bouffard, Boileau, and Vezeau (2001) found that domain-specific self-efficacy in French class decreased from middle to high school and You and Sharkey (2009) found that greater general perceived control in life had positive effects on growth in engagement. Because You and Sharkley only measured perceived control at the baseline, it is unclear how that factor of agency changes and whether its positive influence on engagement remains consistent across multiple years of adolescence. Though that previous work supports a dynamic self-reinforcing system of motivation, engagement, and performance in school (Skinner et al., 2008), limitations from this past work stress the need for improved longitudinal modeling to advance theory and the application of theory to prevention and intervention in practice.

1.5. A more informed picture: analysis of true intraindividual change

Advances have been made in growth modeling with longitudinal repeated measures (Grimm, Mazza, & Mazzocco, 2016). Past research on longitudinal changes in personal agency and engagement have employed some of these techniques to detect within- and between-person effects and time-varying associations between constructs. However, none of the approaches to date have used the *dual change score model* (DCSM) proposed by McArdle (2009). This approach combines the latent growth model with the cross-lagged and latent change models, which allows for all occasions of repeated measures to be considered endogenous and for dynamic associations between variables to be made prominent (Grimm et al., 2016). Notably, this feature allows for more complex investigations about how prior states may predict subsequent change within variables and between variables. Controlling for auto-regressive effects as well as the cross-lagged effects, simultaneously, in a multivariate framework allows for a more precise estimate of longitudinal change in unique but interrelated constructs. To our knowledge, this study represents one of the first applications of DCSM in educational psychology research.

1.6. Aims of present study

In this study, we examined the dynamic structure of personal agency and disengagement and their influence on attendance and academic outcomes during the transition from middle school to high school in several school districts in the Pacific Northwest. Personal agency includes self-efficacy and uncertain control. Disengagement reflects the mortification of affective engagement and the loss of motivation in school. The following research questions and hypotheses guided our study.

1. Is there a significant auto-regressive effect for self-efficacy, perceived control, and disengagement? We expected the dual change score modeling approach to be optimal and illustrate a significant auto-correlative effect for each factor, where prior level in each variable predicts subsequent change.
2. How does multivariate modeling affect initial level, constant change, and the strength of the auto-regressive effect within each factor? Because these variables are theoretically interrelated, we expected that the multivariate modeling would result in changes to some estimates from the univariate models.
3. How much does self-efficacy, perceived control, and disengagement

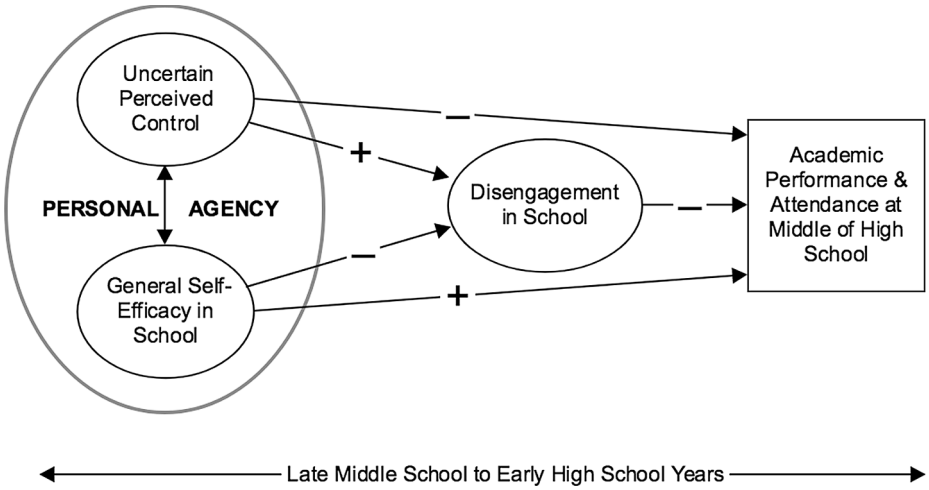

Fig. 1. This study explores the theoretical model where motivational factors of students' personal agency—self-efficacy and perceived control—influence changes in student engagement in school during the late middle school and early high school years and that engagement, in turn, influences academic performance and attendance.

Table 1
Descriptive statistics and Cronbach's alpha reliability for subscales of interest at each of the four measurement waves.

Variable	Measurement wave				
	T1: Fall 8th (n = 5614)	*T2: Spring 8th* (n = 5129)	*T3: Winter 9th* (n = 4688)	*T4: Winter 10th* (n = 4200)	*T5: Spring 10th* (n = 4525)
Adaptive motivation: Self-belief	23.04 (4.22) ∝ = 0.81	22.23 (4.77) ∝ = 0.83	22.08 (4.56) ∝ = 0.84	22.01 (4.68) ∝ = 0.83	–
Maladaptive Motivation: Uncertain control	12.71 (5.68) ∝ = 0.81	12.16 (5.65) ∝ = 0.84	12.36 (5.53) ∝ = 0.85	12.12 (5.38) ∝ = 0.86	–
Maladaptive engagement: Disengagement	8.87 (4.86) ∝ = 0.80	9.85 (5.40) ∝ = 0.85	10.38 (5.44) ∝ = 0.84	10.80 (5.50) ∝ = 0.84	–
Attendance (reverse log transformation)	–	–	–	–	−1.31 (0.46)
Grade Point Average	–	–	–	–	2.70 (0.98)

Note. Due to student attrition across waves, these statistics only account for students whose score was actually observed on that wave. As such, some of these estimates may be biased. To manage these issues of missing data we used Full Information Maximum Likelihood estimation and robust (Huber-White) standard errors in all analyses; estimates of unbiased model parameters are reported in subsequent sections.

Table 2
Correlations of variables included in dual change score model of attribution and self-efficacy model of motivation and engagement.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Uncertain control T1	–													
2. Uncertain control T2	0.58	–												
3. Uncertain control T3	0.49	0.56	–											
4. Uncertain control T4	0.45	0.50	0.56	–										
5. Self-belief T1	−0.28	−0.23	−0.23	−0.23	–									
6. Self-belief T2	−0.24	−0.29	−0.25	−0.24	0.48	–								
7. Self-belief T3	−0.22	−0.24	−0.37	−0.27	0.36	0.42	–							
8. Self-belief T4	−0.21	−0.22	−0.23	−0.33	0.33	0.37	0.45	–						
9. Disengagement T1	0.40	0.31	0.27	0.24	−0.50	−0.36	−0.27	−0.24	–					
10. Disengagement T2	0.26	0.42	0.29	0.27	−0.33	−0.50	−0.32	−0.26	0.52	–				
11. Disengagement T3	0.21	0.26	0.44	0.28	−0.25	−0.33	−0.50	−0.28	0.39	0.51	–			
12. Disengagement T4	0.18	0.21	0.25	0.45	−0.25	−0.30	−0.32	−0.42	0.34	0.42	0.52	–		
13. Attendance (rev. log) T5	0.16	0.16	0.15	0.17	−0.13	−0.14	−0.14	−0.12	0.18	0.15	0.20	0.17	–	
14. GPA 10th T5	−0.35	−0.35	−0.36	−0.37	0.24	0.23	0.29	0.29	−0.24	−0.18	−0.24	−0.23	−0.52	–

Note. T1 = Fall of 8th grade; T2 = spring of 8th grade; T3 = winter of 9th grade; T4 = winter of 10th grade; T5 = spring of 10th grade. All correlations significant at $p < .001$.

change during four waves of data? Based on past research, we expected self-efficacy to decrease and uncertain control and disengagement to increase across the middle school to high school transition.

4. How does level of self-efficacy, perceived control, and disengagement influence subsequent change in other factors (i.e., cross-lagged effects)? We expected to find reciprocal effects between the two factors of agency, where an increase in self-efficacy might benefit perceived control, for example (see Fig. 1 for an illustration of our hypotheses). Though agency factors should influence engagement, reciprocal effects between disengagement and personal agency were less plausible. Theory would suggest that disengagement is likely to contribute to greater loss of control—the more disengaged students become, the less in control they may feel about their academic performance. Though less immediate than in the case of control, disengagement could also lead to lower levels of general academic self-efficacy. However, because disengagement represents a loss of motivation, highly disengaged students may not be invested enough to feel a strong loss of self-efficacy or perceived control. In fact, their disengagement may be an act of agency—to detach from an

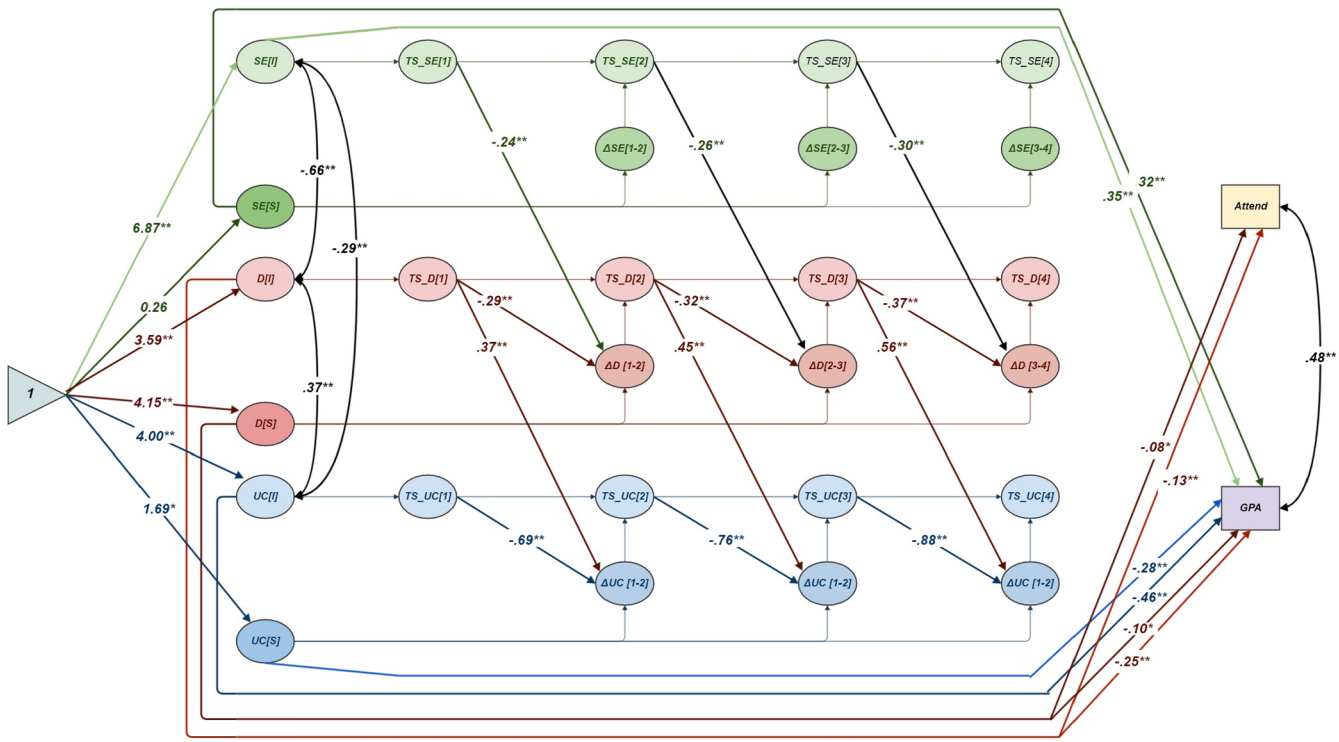

Fig. 2. Trivariate DCSM predicting distal attendance and GPA outcomes (standardized). $^{*}p < .05$, $^{**}p < .01$. SE = Self-efficacy; D = Disengagement; UC = Uncertain control.

Table 3
Univariate LGCA and DCSM for self-efficacy, disengagement, and uncertain control predicting distal attendance and GPA.

Fit indices	Self-efficacy		Disengagement		Uncertain control	
	LGCA	DCSM	LGCA	DCSM	LGCA	DCSM
χ^2 (*df*)	285.47** (13)	260.70** (12)	271.55** (13)	229.23** (12)	238.94** (13)	90.85** (12)
$\Delta\chi^2$ (Δdf)		24.77** (1)		42.32** (1)		148.09** (1)
BIC	128,761.43	128,745.36	133,750.21	133,725.29	134,101.91	133,962.52
CFI	0.95	0.95	0.96	0.97	0.97	0.99
RMSEA	0.06	0.06	0.06	0.06	0.05	0.03
SRMR	0.05	0.05	0.05	0.04	0.04	0.02
Parameter estimates						
θ[I]	19.86**	19.92**	12.80**	12.70**	18.02**	17.93**
ϕ[I]	6.75**	7.85**	10.24**	11.60**	12.00**	16.26**
θ[S]	−0.78**	0.74*	1.11**	3.69**	−0.04	2.60**
ϕ[S]	0.32**	0.62**	0.86**	1.73**	0.23**	1.02**
α[I] − Attend	0.24	0.24	−1.00**	−0.98**	0.17	−0.16
α[I] − GPA	1.00**	0.99**	−0.92**	−0.92**	−2.13**	−2.08**
α[S] − Attend	−0.10	−0.08	−0.10	−0.31**	−0.05	−0.03
α[S] − GPA	0.18**	0.28**	−0.08*	−0.27**	−0.02	−0.31**
βFactor − ΔFactor		−0.08**		−0.19**		−0.14**

Note. θ[I] & θ[S] = factor intercept and slope means, ϕ[I] & ϕ[S] = factor intercept and slope residual variance, α[I] & α[S] − Attend & GPA = influence of factor intercept and on distal attendance and GPA outcomes, βFactor − ΔFactor = auto-regressive effect, CFI = Comparative Fit Index (adequate fit > 0.95), RMSEA = Root Mean Square Error of Approximation (adequate fit < 0.06), SRMR = Standardized Root Mean Square Residual (adequate fit < 0.08) (Hu & Bentler, 1999). All parameters are reported with unstandardized results. The sign for attendance has been reversed to correct for the reverse log transformation and allow accurate interpretations.

** $p < .01$.

* $p < .05$.

environment that does not meet their needs. Our hypotheses about reciprocity between agency and engagement are exploratory.

5. Do the degree of personal agency and disengagement at the beginning of Grade 8, and change experienced in the following three years, predict attendance and GPA at the end of Grade 10? Given the research reviewed on factors of personal agency, both self-efficacy and control should relate directly to higher academic performance even when controlling for the potentially mediating role of disengagement. Due to the proximal link between affective disengagement and behavioral disengagement (school absence) disengagement is more likely to relate to lower attendance than the factors of personal agency. Though research is limited on the link between personal agency and school attendance, we believed that a small, positive association may be found.

Table 4
Bivariate and trivariate DCSM for self-efficacy, disengagement, and uncertain control predicting distal attendance and GPA outcomes.

Fit indices	Bivariate			Trivariate
	SExD	SExUC	DxUC	SExDxUC
χ^2 (*df*)	524.75** (36)	401.52** (36)	392.49** (36)	704.95** (72)
BIC	241,457.92	244,324.15	247,496.84	355,129.47
CFI	0.97	0.97	0.98	0.97
RMSEA	0.05	0.04	0.04	0.04
SRMR	0.05	0.03	0.03	0.04
Parameter estimates				
Self-efficacy (SE)				
θSE[I]	19.88**	20.00**		19.95**
ϕSE[I]	7.39**	7.79**		7.42**
θSE[S]	0.01	0.92**		0.17
ϕSE[S]	0.39**	0.59**		0.39**
αSE[I] − Attend	0.26	0.25		0.28
αSE[I] − GPA	0.99**	0.96**		0.95**
αSE[S] − Attend	−0.09	−0.08		−0.09
αSE[S] − GPA	0.24**	0.26**		0.26**
βSE − ΔSE	−0.04	−0.08**		−0.05
Disengagement (D)				
θD[I]	12.74**		12.68**	12.69**
ϕD[I]	11.39**		11.44**	11.11**
θD[S]	4.71**		2.04**	4.20**
ϕD[S]	1.17**		1.15**	1.00**
αD[I] − Attend	−0.98**		−0.99**	−0.98**
αD[I] − GPA	−0.92**		−0.89**	−0.90**
αD[S] − Attend	−0.21*		−0.18*	−0.18*
αD[S] − GPA	−0.08		−0.15**	−0.11*
βD − ΔD	−0.12**		−0.06**	−0.08**
Uncertain control (UC)				
θUC[I]		17.90**	17.94**	17.90**
ϕUC[I]		16.30**	15.97**	16.02**
θUC[S]		4.66**	1.53**	1.55*
ϕUC[S]		0.97**	0.79**	0.78**
αUC[I] − Attend		0.18	0.18	0.18
αUC[I] − GPA		−2.07**	−2.08**	−2.06**
αUC[S] − Attend		−0.02	0.08	−0.09
αUC[S] − GPA		−0.25**	−0.26**	−0.26**
βUC − ΔUC		−0.16**	−0.17**	−0.17**
Cross-lagged parameters				
γD − ΔSE	< 0.01			< 0.01
γSE − ΔD	−0.10**			−0.08**
γSE − ΔUC		−0.09**		< −0.01
γUC − ΔSE		−0.01		−0.01
γUC − ΔD			< 0.01	−0.02
γD − ΔUC			0.11**	0.11**

Notes. All parameters are reported with unstandardized results. SE = Self-efficacy; D = Disengagement; UC = Uncertain control. θFactor[I] = initial level, ϕFactor [I] = initial level residual variance; θFactor[S] = constant change, ϕFactor[I] = constant change residual variance; αFactor[I] − Attend/GPA = influence of initial level on distal attendance/GPA outcomes; αFactor[S] − Attend/GPA = influence of constant change on distal attendance/GPA outcomes; βFactor − ΔFactor = autoregressive effect of level in factor on subsequent change within factor; γFactor − ΔFactor = cross-lagged effect of level in factor on change in different factor.

** $p < .01$.

* $p < .05$

2. Materials and methods

This study used data collected as part of the Middle School Intervention Project (MSIP), a federally funded Evaluation of State and Local Education Programs and Policies to examine the impact of systemic literacy and engagement interventions in middle school; however, all analyses in this study pool students across treatment and comparison conditions. The research questions investigated in this study were separate from the primary purpose of MSIP to evaluate the impact of district-provided reading and engagement interventions on reading outcomes. We used measurement invariance testing (e.g. Vandenberg & Lance, 2000) to evaluate the influence of the intervention and found no substantive effects.

2.1. Participants

The sample for this study was drawn from six districts in the Pacific Northwest and included 6,077 students who attended 25 middle schools in Grade 8 in 2013. Students were included in the analytic sample if they had complete data for the variables of interest for at least one of the four waves included in this study. Across the sample, 1.7% of students identified as American Indian/Alaska Native, 5.7% Asian, 2.3% Black/African American, 22.6% Hispanic, 5.5% multiracial, 1.0% Native Hawaiian/Pacific Islander, 58.7% White, and 2.5% declined to report their race/ethnicity. Additionally, 48.5% of the sample was female, 13% of students received special education services in Grade 8, and 10.2% were emergent bilingual students with limited English language proficiency in Grade 8.

2.2. Data collection

Data were collected using an online survey platform, or paper version if needed, during normal school hours. Students had the option of reading or listening to survey questions. At each measurement occasion, students completed the survey during a three-week window. Teachers administered the survey after receiving instructions from the research team on proper administration. Students were given assurance that their responses would be anonymous to faculty and peers. Following procedures approved by the Institutional Review Board, additional school-based demographic, achievement, and behavioral data were collected from districts.

2.3. Measurement

The Motivation and Engagement Scale – Junior School (MES) (Martin, 2007, 2009, 2011, 2014) is a 44-item survey instrument designed to measure a student's motivation and engagement. Extensive research has been conducted demonstrating strong evidence of reliability for the MES and its subscales. These studies have validated the use of the MES in the research of motivation and engagement as predictors of important school outcomes (Martin, 2014).

2.3.1. Instruments

All items on the MES were measured on a seven-point Likert-type scale (1 = disagree strongly to 7 = agree strongly). Scoring procedures were followed as outlined in the technical assistance documentation for the MES (Martin, 2012). To compute a subscale score for self-efficacy and uncertain control, the four item responses for each subscale were summed to form a score in the range of 4–28, where a score of "4″ represented students responding with a "1" to all four subscale items and a score of "28" represented students responding with a "7" to all four items. If students provided responses to only three of the four items for each subscale then we multiplied that sum score by 4/3 (e.g., $1.\bar{3}3$), accounting for the missing response with the average of the three responses completed for that subscale. If students provided responses to less than three items then the value was not scored for the subscale. All descriptive statistics for all subscales are in Table 1—internal consistency for subscales at each wave was good ($\propto > 0.80$)—and Table 2 presents correlations of predictor and outcome variables.

2.3.1.1. Student agency. Of the six subscales on the MES measuring *adaptive* motivation and engagement (i.e., factors that positively relate to student success), we included *self-efficacy*. Self-efficacy included four items measuring a student's perception of his or her ability to do well in school with enough effort (i.e., If I try hard, I believe I can do my schoolwork well). Of the three subscales on the MES measuring maladaptive motivation (i.e., cognitive and affective factors that detract from student success), we included *uncertain control* as the maladaptive form of perceived control. Uncertain control included four items measuring how much a student perceived their academic performance to be outside their sense of control (i.e., When I don't do well at school I don't know how to stop that happening next time).

2.3.1.2. Disengagement. In our model, we included one subscale on the MES that measures maladaptive engagement and loss of motivation. *Disengagement* included four items targeting affective engagement toward school to measure the degree to which a student cares about, feels involved, and is interested in school (i.e., Each week, I'm trying less and less at school).

2.3.2. Academic performance

In this study, student grade point average (GPA) served as a proxy for academic performance. Marks (2000) classified GPA as *orientation to school*, pointing out that GPA accounts for the many non-academic factors that go into school grades, including student participation in class, working to potential, homework completion, relationship to teachers and peers, and other behavioral aspects of classwork. Although teacher grading has shown to be an inconsistent practice within and between schools (McMillan, 2003) and some researchers discourage the use of GPA in education research (e.g., Graham, 2015), GPA still serves as one of the strongest predictors of college success (Geiser & Santelices, 2007) and provides a broadly encompassing evaluation of student relation to academic work and the classroom environment. Moreover, GPA has demonstrated lower correlations to confounding socioeconomic variables than standardized college admission tests and has explained greater variance in students' fourth year college grade point average than standardized tests (Geiser & Santelices, 2007). Given this evidence of predictive and consequential validity and the fact that GPA captures academic, interpersonal, and intrapersonal orientation to school, GPA presented a more holistic outcome measure than standardized achievement scores. Because GPA did not violate assumptions of normality, we calculated GPA on a zero to four continuous scale representing the cumulative reported high school academic achievement for each student at the end of Grade 10. GPA scores included grades from across students' school performance, including classes (e.g., physical education) that are less traditionally academic in nature.

2.3.3. School-based behavior

Following the research on dropout prevention and behavioral disengagement in school (e.g., Balfanz et al., 2007), and the strong predictive nature of attendance on high school success, attendance served as a marker that was likely to be important in the trajectory of student engagement. For this study, attendance was included as an outcome variable that identified the percent of school days attended in Grade 10.

2.4. Analytic strategy

All hypotheses were tested using a trivariate dual change score model (DCSM; McArdle, 2009) using the Lavaan package (Rosseel, 2012) in *R* open access software (see Appendix B for the code used to conduct analyses). As a specialized longitudinal structural equation modeling analytic technique, DCSM expands on the well-established longitudinal growth curve (e.g., Preacher, Wichman, MacCallum, & Briggs, 2008) and latent difference score (e.g., McArdle, 2001) approaches (Ghisletta & Lindenberger, 2005). DCSM evaluates the degree to which the level of each construct predicts change in the same construct at subsequent time-points (i.e., auto-regressive effects), controlling for regression-to-the-mean and ceiling/floor effects, as well as the degree to which level of a variable predicts change in another variable at subsequent time-points (cross-lagged effects; Grimm et al., 2016; McArdle, 2009). Exploring these relations within a latent construct structure disaggregates residual variance, including measurement error, from the constructs to calculate a "true score" (Kline, 2011, p. 213). For more background information and explanation of univariate and trivariate DCSMs, refer to the narrative and Figs. A1 and A2 in Appendix A accompanying this study.

We used Full Information Maximum Likelihood estimation and robust standard errors (Freedman, 2006) in all analyses, which can provide unbiased estimates in the presence of missing and/or non-normal data. To evaluate how the data fit each model, we used Hu and Bentler (1999) criteria for close fit. Although students were clustered within schools in our sample, we chose not to run analyses as multilevel models due to the highly complex and novel nature of the analytic design. Moreover, the fact that students transitioned from being clustered in middle schools to being differently clustered in high schools at the midpoint of the data waves would have added an additional layer of complexity to the analysis and interpretation of effects. As a sensitivity analysis, we ran a two-level unconditional model, students within schools, for the distal outcomes, attendance and GPA, to determine the size of the Intraclass Correlation Coefficients (ICCs). For both outcomes, the ICCs were approximately 0.07. According to Hedges and Hedberg

(2007), an ICC of that magnitude is at the low end of the ICC range for studies that included schools with varying levels of achievement. In contrast, Hedges and Hedberg found an average ICC of 0.22 for all studies they analyzed. Given the small amount of variance explained at the school level and the challenge of converging multilevel DCSM models, our study assumes that patterns do not vary considerably across schools. As more researchers apply the DCSM modeling technique, developing robust procedures to test hierarchical models will be needed.

When comparing nested models, we assessed change in model fit using both the traditional chi-square difference test (Kline, 2011) and change in Baysian Information Criterion (BIC). Unlike the chi-square difference test, comparing BIC of nested models penalizes for an increase in the number of estimated parameters, as this will often improve model fit. Thus, this information theoretic approach discourages overfitting the model to the data (Kass & Wasserman, 1995). Additionally, in other similarly complex latent class models, research suggests BIC outperforms other fit indices under the conditions that the nested structure of the data is ignored, the interclass correlation is low, and the sample size is large (e.g. Chen, Luo, Palardy, Glaman, & McEnturff, 2017), as is the case with the present study. When comparing nested models, lower BIC indicates better model fit; however, there is no empirical statistical significance test of difference in BIC. For this reason, when the result of the chi-square difference test and change BIC disagree, we reported both results but follow the results of the chi-square difference test. We measured effect sizes (Cohen, 1992) using standardized regression coefficients ($r = 0.10$, small effect; $r = 0.30$, medium effect; $r = 0.50$, large effect).

3. Results

Prior to testing our hypotheses with our proposed analytic techniques, we tested the assumption of normality for all variables included in the model. Given that the *z*-score for kurtosis and skewness were below the threshold of +/-2 for all variables, except for attendance, variables did not violate the assumptions of normality. For attendance, which was severely negatively skewed and leptokurtotic as expected, we used a reverse score log transformation. We conducted a reverse score log transformation by adding 1 to each attendance percentage, subtracting those from 2 and taking the log transformation to base 10 (Field, 2009). This transformation improved skewness and kurtosis substantially; however, it also inverted the scores. To simplify interpretations, we reversed all reported parameters associated with attendance results reported in this study to ensure accurate interpretation. The descriptive statistics of the variables of interest are included in Table 1. The bivariate Pearson correlation between each variable is reported in Table 2. All estimates provided in text and tables are unstandardized estimates; all estimates provided in Fig. 2 are standardized.

Using the *BaylorEdPsych* package (Beaujean, 2012) in *R* software, we explored missing data patterns and found that the data violated assumptions of missing completely at random; $\chi^2(389) = 1248.80$, $p < .01$. Not surprisingly, the rate of missing data on variables measuring personal agency factors and engagement factors increased over measurement occasions. For instance, on the self-efficacy measure at the beginning of Grade 8, 463 (or 7.6% of) cases were missing a score. By the final wave in the middle of Grade 10, 1877 (or 30.8% of) cases were missing scores. Similarly, for our distal outcomes, GPA and school attendance at the end of Grade 10, 1552 and 1605 cases (or 25.5% and 26.4%) were missing, respectively. We used logistic regression to identify potential instrumental variables in systematic missingness. We found that student gender did not predict missingness on variables included in the model. Though special education status and limited English proficiency status did not relate to missing data on GPA or attendance, both predicted a greater likelihood of missing data on all waves of motivation and engagement factors. This issue may have been due to the fact that students identified for either special education or limited English proficiency were less likely to take the survey due to language or comprehension barriers. Given that data for key variables were not missing at random, parameters may be biased. To investigate, we conducted the same analysis described below, using multiple imputation procedures in *R* software using the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011). We found that all patterns held and that regression weights increased; thus, reported parameters may be underestimated.

3.1. RQ1: is there a significant auto-regressive effect for self-efficacy, perceived control, and disengagement?

To answer our first research question, we compared univariate latent growth curve models (LGCM) and dual-change score models (DCSM) for self-efficacy, perceived control, and disengagement. We present model fit and parameter estimates in Table 3. In comparing model fit, the DCSM statistically significantly outperformed the LGCM and the auto-regressive effect (βFactor − ΔFactor) was significant for each factor. After controlling for the auto-regressive effect, change in uncertain control went from being non-significant to increasing across measurement occasions. Additionally, after controlling for the auto-regressive effect, change in disengagement went from not having an effect on student's Grade 10 attendance to being associated with a statistically significant declination. The benefit of including auto-correlative effects in the dual change score approach improved model fit, increased precision of estimates, and clarified whether or not growth or declination existed.

3.2. RQ2: how does multivariate modeling affect initial level, constant change, and the strength of the auto-regressive effect within each factor?

To answer our second research question, we fit bivariate DCSMs for each unique pair of factors – self-efficacy with disengagement (SExD), self-efficacy with uncertain control (SExUC), and disengagement with uncertain control (DxUC) – and a trivariate DCSM for all three factors (SExDxUC) in order to examine the influence of each factor on initial level, constant change, and strength of auto-regressive effects within each of the other factors. For all of the following reported results, we present model fit and unstandardized parameter estimates of each model in Table 4. We present standardized parameter estimates in Fig. 2. All models successfully converged and achieved close fit (SExD $\chi^2 = 524.75$, $df = 36$, BIC = 241,457.92; SExUC$\chi^2 = 401.52$, $df = 36$, BIC = 244,4324.15; DxUC $\chi^2 = 392.49$, $df = 36$, BIC = 247,496.84, SExDxUC $\chi^2 = 704.95$, $df = 72$, BIC = 355,129.47).

The inclusion of different combinations of factors substantially affected initial levels, constant change, and the strength of the auto-regressive effects for several factors, progressively gaining in precision. We detail the most notable results below and in Table 4. Whereas the slope for self-efficacy was significantly positive in both the univariate model, with self-efficacy on its own, (θSE[S] = 0.74, $p < .05$) and the SExUC bivariate model (θSE[S] = 0.92, $p < .01$), it was non-significant after controlling for the influence of disengagement both in the bivariate SExD model (θSE[S] = 0.01, $p > .05$) and the trivariate model (θSE[S] = 0.17, $p > .05$). Similarly, the auto-regressive effect of level of self-efficacy on subsequent change in self-efficacy was both negative and significant in the univariate (βSE − ΔSE = −0.08, $p < .01$) and SExUC bivariate model (βSE − ΔSE = −0.08, $p < .01$), but non-significant after controlling for the influence of disengagement in both the bivariate SExD model (βSE − ΔSE = −0.04, $p > .05$) and trivariate model (βSE − ΔSE = −0.05, $p > .05$). In comparison to the univariate model (αD[S] − GPA = −0.27, $p < .01$) the influence of constant change in disengagement on the distal GPA outcome was attenuated for both the bivariate SExD (αD[S] − GPA = −0.08, $p > .05$) and DxUC (αD[S] − GPA = −0.15, $p < .01$) models in addition to the trivariate model (αD[S] − GPA = −0.11, $p < .05$). The rate of constant change in uncertain control appeared to decrease after

controlling for the influence of disengagement in both the trivariate model (θUC[S] = 1.55, $p < .05$) and bivariate DxUC model (θUC[S] = 1.53, $p < .01$) as compared to the SExUC bivariate model (θUC[S] = 4.66, $p < .01$) or univariate model (θUC[S] = 2.60, $p < .01$). The influence of level of self-efficacy on subsequent change in uncertain control was attenuated by the influence of disengagement on both factors when comparing the trivariate model (γSE − ΔUC < −0.01, $p > .05$) to the SExUC bivariate model (γSE − ΔUC = −0.09, $p < .01$). As the results demonstrated, a multivariate dual change score approach achieved greater clarity in how individual agency and engagement factors changed over time when controlling for the cross-lagged effects of other factors that were theoretically related for students in adolescence.

3.3. RQ3: how much does self-efficacy, perceived control, and disengagement change during four waves of data in the trivariate model?

To answer our fourth research question, we examined constant change (θFactor[S]) for each factor within the trivariate DCSM. When controlling for auto-regressive and cross-lagged influences in the dual change score approach, students did not experience significant change in self-efficacy across the four measured time points (θSE[S] = 0.17, $p > .05$). This change suggests that our earlier finding of positive growth in self-efficacy detected in the less complex univariate models may be misleading when considered in isolation. That result underscores the analytic power of a latent change, multivariate modeling approach when dealing with conceptually and empirically related variables. Students did experience a significant increase in both disengagement (θD[S] = 4.20, $p < .01$) and uncertain control (θD[S] = 1.55, $p < .05$) across the four measured time points between Grades 8–10.

3.4. RQ4: how does level of self-efficacy, perceived control, and disengagement influence subsequent change in other factors in the trivariate model?

To answer our third research question, we examined the cross-lagged parameters (γFactor − ΔFactor) measuring the influence of level within each factor on subsequent change in other factors within the trivariate DCSM. We found that higher levels of self-efficacy related to a declination in disengagement with a small effect (γSE − ΔD = −0.08, $p < .01$), but there was no reciprocal influence of disengagement on change in self-efficacy (γD − ΔSE < 0.01, $p > .05$). Additionally, level of self-efficacy did not influence subsequent change in uncertain control (γSE − ΔUC < −0.01, $p > .05$), nor did level of uncertain control influence change in self-efficacy (γUC − ΔSE = −0.01, $p > .05$). Higher disengagement related to an increase in uncertain control at a small effect (γD − ΔUC = 0.11, $p < .01$), but level of uncertain control did not relate to increased disengagement (γUC − ΔD < 0.01, $p > .05$). Using the dual change score approach clarified directionality of influence among factors, which added to our confidence in estimates generated.

3.5. RQ5: do the degree of personal agency and disengagement at the beginning of Grade 8, and change experienced in the following three years, predict attendance and GPA at the end of Grade 10 in the trivariate model?

To answer our fifth research question we examined the influence of initial level and constant change in self-efficacy, disengagement, and uncertain control on distal Grade 10 attendance and GPA outcomes. We found that initial level and constant change in self-efficacy exerted a significant positive influence on the distal GPA outcome (αSE[I] − GPA = 0.95, $p < .01$; αSE[S] − GPA = 0.26, $p < .01$), at a medium effect; however, neither the intercept nor slope of self-efficacy influenced change in subsequent attendance (αSE[I] − Attend = 0.28, $p > .05$; αSE[S] − Attend = −0.09, $p > .05$). Similarly, initial level (a large effect) and constant change (a medium effect) in uncertain control exerted a negative influence on the distal GPA outcome (αUC[I] − GPA = −2.06, $p < .01$; αUC[S] − GPA = −0.26, $p < .01$) but did not influence attendance (αUC[I] –Attend = 0.18, $p > .05$; αUC[S] –Attend = 0.09, $p > .05$). Initial level and constant change in disengagement exerted a significant negative influence on distal GPA, medium and small effects, respectively, (αD[I] − GPA = −0.90, $p < .01$; αD[S] − GPA = −0.11, $p < .05$). Initial level and constant change in disengagement exerted a significant negative influence on attendance, a small effect (αD[I] − Attend = −0.98, $p < .01$; αD[S] − Attend = −0.18, $p < .05$). Generally, those results supported our hypotheses and indicated that both personal agency and affective engagement play unique roles in shaping performance in school.

4. Discussion

In this study, we set out to provide more clarity about how students' personal agency might mitigate the the trend of increasing disengagement, and its direct negative influence on academic performance, during the end of middle school and first half of high school. We examined the unique influence of two aspects of personal agency on subsequent change in one another, and on disengagement, to provide a more precise theoretical contribution about directionality and degree of influence. We increased analytic complexity in stages, proceeding from univariate LGCM to univariate DCSM and bivariate DCSM, and concluding with trivariate DCSM to understand how this progression affected results and to identify the most precise estimates. Methodologically, that process underscored the benefits of incorporating the cross-lagged and autocorrelative effects with the dual change score approach. For instance, the slope for self-efficacy across the three years of interest changed in each model, demonstrating a negative trend, positive trend, and finally no statistically significant change at all. Gains in precision provided a more accurate development of theory about changes in personal agency and engagement during adolescence. Our findings complement existing theory on the process and effects of disengagement across K-12 schooling and contribute to recent research on the composition and role of students' personal agency.

While most of our hypotheses were supported, specific nuances require further consideration. First, auto-correlative effects were significant for all three factors, supporting our first hypothesis. Second, as hypothesized, the profile of each factor changed to some degree when progressing from univariate to multivariate models. The most profound shift was found with self-efficacy. When controlling for cross-lagged effects of disengagement and uncertain control and auto-regressive effects of prior level, self-efficacy did not appear to decline or increase. Notably, the positive slope indicating increased self-efficacy in the univariate models was neutralized when controlling for cross-lagged effects. That finding contrasts with decreasing trends in self-efficacy that others have found (e.g., Bouffard et al., 2001). Third, as expected, disengagement and uncertain control increased across the middle to high school period studied; however, in contrast to our hypotheses, general self-efficacy demonstrated no change when controlling for all of the possible influences in the trivariate DCSM.

Fourth, only some of our hypotheses regarding between factor influences were supported empirically. Though some cross-lagged effects were statistically significant, they were unidirectional. In the trivariate model, perceived control did not influence change in disengagement; however, level of disengagement influenced subsequent change in perceived control across at all three time intervals. As hypothesized,

students who were more disengaged perceived a weakening sense of control about their ability and performance in school; however, in contrast to our hypothesis, students did not necessarily become more disengaged as a result of lower perceptions of control. Disengagement appeared to influence, directly, the aspect of personal agency related specifically to sense of control. Students only became more disengaged without the resilience factor of stronger self-efficacy, and disengagement did not influence change in self-efficacy. Our results also showed that self-efficacy and perceived control may not influence change in one another. Those results reinforce Bandura (1986) emphasis in SCT that self-efficacy is foundational to how personal agency affects interest and engagement in tasks within a learning environment. The results further suggest that these two primary factors of personal agency relate to one another but may function separately during the early to middle period of adolescence.

Fifth, perceived control related directly to school performance at the middle of high school. Because its role in agency does not appear to result in changes to disengagement, it is possible that lower perceived control influences academic performance through adaptive factors such as persistence or capacity to plan and set goals or maladaptive factors such as failure avoidance. As hypothesized, both initial levels and change over time in affective engagement and general self-efficacy influenced GPA at the middle of high school. Further reflecting our hypotheses, affective engagement—both beginning level in Grade 8 and change over time—was the only factor to influence the behavioral engagement of school attendance.

4.1. The substantial role of personal agency

Based on the estimated effect sizes reported from the trivariate model, the actual influence of disengagement on academic performance appears to be weaker than the role of personal agency. As the results indicated, the strength of the relationship between disengagement and academic performance appeared to decrease by more than half from the univariate DCSM to the trivariate DCSM, demonstrating substantial variance explained by personal agency that overlapped with disengagement. This precision is a result of the chosen modeling technique, where the *true intraindividual change* and unique shared variance of each distinct construct with other constructs becomes specified (McArdle, 2009). Given these relations, a self-reinforcing cycle of motivation, engagement, and performance emerges. Our results indicate that when student's self-efficacy drops, disengagement in school increases during the years transitioning to high school. Increased disengagement weakens perceived control, and change in both the control and self-efficacy dimensions of personal agency are the main drivers of school performance in this model. Increased disengagement leads to lower attendance, and the research is clear that decreased attendance in high school increases the risk of dropping out (e.g., Balfanz et al., 2007).

Notably, the process revealed by our models does not support the notion that motivation underlies engagement and engagement leads to performance as past research has suggested (Martin, 2012). While that notion may be true to a degree, the motivational factors of personal agency play a direct role in student performance—a role as large or larger than engagement. Perhaps these factors are too tightly intertwined for the individual within the complex sociocultural setting of secondary school to be disentangled in theory. As SCT argues and substantial past research confirms (Bandura, 1986, 2006), the two key ingredients of personal agency that we investigated contribute substantially to school engagement and academic performance during the dynamic period of adolescent development.

4.2. Middle school matters

Given that self-efficacy appears to exert a strong influence on disengagement across these three transition years, self-efficacy is likely a particularly powerful ameliorative factor to protect against disengagement, as others have found (Madjar & Chohat, 2017). In contrast, the influence of disengagement on change in perceived control across those years indicates that disengagement may become an increasingly powerful destabilizing factor and result in further degradation of agency. Notably, the power of those negative shifts in agency and engagement go back to middle school. The strong influence of middle school self-efficacy that we detected indicates a stable pattern that begins early, possibly as early as middle school entry, as other research suggests (e.g., Balfanz et al., 2007). Though scholars focused heavily on the effects of developmentally inappropriate middle school environments two decades ago (e.g., Roeser & Eccles, 1998), middle level educational environments have changed little (West & Schwerdt, 2012) and continue to have a negative effect on students' self-beliefs and perceptions (Madjar & Cohen-Malayev, 2016; Madjar & Chohat, 2017), which our results show persist across three pivotal secondary school transition years. Based on their findings, Madjar and Chohat (2017) suggested one seemingly simple but important adjustment that teachers can make to affect positive results on students' self-efficacy and the school environment—emphasize individual development toward mastery rather than competition among students. As our results indicate, the resulting improvements in students' perceived agency could exert an influence into high school and, potentially, far beyond.

4.3. Implications for intervention

Our findings have relevance for practice, but we caution that (a) the modeling approach is associational, (b) we only included a few factors and many others could be important, and (c) the relationship between agency, engagement, and academic performance may be reciprocal. As such, recommendations are provided as considerations not prescriptions. In line with Martin et al. (2017) suggestions, our findings indicate that interventions that target academic skills, affective engagement, and personal agency together may be more effective during the high school transition years. Additional factors that fit within the SCT perspective on personal agency could be important to consider in the design of interventions. For instance, interpersonal agency depends on relational support from others (Martin et al., 2017); therefore, developing stronger peer-to-peer and student-to-teacher relationships alongside personal agency and academic skills could enhance effects. Building on Usher and Pajares (2006) findings, we recommend that early interactions with students in middle and high school (a) provide mastery experiences, (b) create social opportunities for encouraging feedback from teachers and peers on the path to mastery, (c) include consistent adult modeling and messaging that the new challenges of high school are normative, and (d) structure explicit opportunities for students to see self-efficacy developed and modeled.

Our findings reinforce the idea that engagement results, in part, from a sense of personal agency in school. Attendance interventions that focus on preventing student disengagement may be more successful if combined with aspects of personal agency. As Burger and Walk (2016) discovered, our findings also suggest that personal agency, through self-efficacy, may be a powerful protective lever of resilience to disrupt patterns of disengagement, poor academic performance, and even factors far outside of the students control, such as generational poverty. Middle and high schools might consider how their culture, systems, and structures reinforce or unintentionally degrade students' personal agency from the first moment they walk through the door. Given the diversity of talents, interests, and cultural backgrounds of U.S. students, access to a broad curriculum that builds self-efficacy and other aspects of personal agency may be critically important to maintaining student engagement. For instance, Thomas, Singh, and Klopenstein (2014) found that enrollment in even just one art class in

high school linked to substantially lower risk of dropping out. It is possible that engagement in the arts during school develops critical aspects of personal agency that generalize to other school experiences. Experiences across the curriculum can provide a similar reinforcement if designed to cultivate and reinforce a student's personal agency.

4.4. Limitations and future directions

Several limitations should be noted that caution interpretation of results. The mono-method self-report assessment could be augmented with other data sources in future studies. These results may differ by context, so generalizability beyond the sample should be made with caution. Moreover, the decision to forgo multilevel analyses limits our ability to detect any potential school-level contextual effects. Our design was not sensitive enough to detect a change in patterns due to the high school transition. More measurement occasions prior to the transition to high school would allow for a piecewise model that might more accurately detect changes in status and rate of change. Methodologically, DCSM needs more attention by researchers in the education field to fill the gaps we have left. For instance, we did not include covariates as mediating or moderating variables in the model itself, and researchers have choices about where to account for these variables. While these additional paths would complicate an already complex model, they may result in more concrete interpretations and applications. The addition of an instrumental variable, such as participation in a treatment condition, could be incorporated in the model at latent change scores, slopes, intercepts, or through invariance testing.

We operationalized self-efficacy and perceived control as generalized constructs, so additional research using similar modeling could investigate these aspects of personal agency in specific tasks and domains. To simplify the model, we did not control for prior levels of GPA or attendance nor for potential reciprocal paths between these outcomes and personal agency and disengagement. Self-system theory would suggest reciprocity may be likely, which will be important to test in future iterations of this kind of modeling, when possible. For further theoretical clarity, future analysis can focus in several directions. First, research should investigate measurement invariance in the motivational and agentic constructs of interest across adolescence to see if the constructs can be stably measured during this dynamic period. Second, research should investigate the invariance of this model of personal agency, engagement, and academic performance across populations of students that experience middle and high school differently, such as English language learners and students with exceptionalities.

4.5. Conclusion

Our findings revisit the important role that middle school plays in students' educational trajectory. Personal agency—especially self-efficacy—fostered during middle school and into high school, can reinforce students' school engagement and academic performance, while engagement in school can support better attendance in high school. Students' engagement plays a role in how perceived control over academic performance changes during the high school transition years and that sense of control plays a role in later academic performance. Those findings can inform how researchers study SCT and human agency in educational settings and longitudinally, using rigorous modeling techniques to push complex socio-psychological theories in education forward and apply them to school interventions and the establishment of an optimal learning environment for adolescent learners. For educators and practitioners who aim to support students' healthy development for success in school, our findings suggest that student agency in learning warrants serious attention.

5. Author's note

This research used data collected in a project supported by a grant from the Institute of Education Sciences, U.S. Department of Education (PR/Award No. R305E100043), to the University of Oregon. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education. We would like to thank Dr. Mark Van Ryzin for his invaluable support and encouragement in applying DCSM to the context of this study.

Appendix A. Clarifications on dual change score model

To help understand DCSM features, we present in Fig. A1 in the Appendix A diagram for a DCSM applied to a single variable in our model. *Self-efficacy* was measured at four time points and is represented by the four squares, marked *Self-efficacy[1]* through *Self-efficacy[4]*. A second term, the true score of self-efficacy demarcated *TS_SE[1]-TS_SE[4],* is then extracted from each measurement occasion to disaggregate variance predicted by the model from unrelated residual variance. The model assumes this residual variance neither changes nor correlates over time. Predicted change, or the *latent change score*, from *TS_SE[1]* to *TS_SE[2]* was demarcated Δ*SE[1–2]*. The parameter labeled β*SE[1–2]* represents the amount of change from *TS_SE[1]* to *TS_SE[2]* explained by level at *TS_SE[1]*. The strength of this approach is that it accounts for regression-to-the-mean and ceiling/floor effects, both significant issues when analyzing change scores in general. Two additional latent factors are extracted, an intercept value representing an individual's initial score (*SE[I]*) and a slope term (*SE[S]*). The population mean intercept and slope term is expressed by the regression weights θ*SE[I]* and θ*SE[S]* from the constant term, represented as the triangle with the label '1.'

In Fig. A2, we present the trivariate DCSM for the present study to illustrate the paths included in the model. Although the model may appear complex, it is merely an expansion of the above model to include the influences and changes of two additional variables. In addition to the auto-correlative effects within each variable over time (represented by regression weights demarcated βfactor), this model allows analysis of the cross-lagged influence of one variable on change in another variable at a subsequent time point represented by regression weights demarcated Υa-b where a and b demarcate the first letter of the influencing variable and influenced variable, respectively. Correlations between factors are similarly labeled ρa-b. Intercept and slope terms, labeled θfactor[I] and θfactor[S] respectively, are extracted next. The intercept term represents the true score intercept in the absence of unexplained variance; deviations from the measured intercepts would suggest some degree of unbalanced residual variance in the model. The slope term represents the predicted, constant change after controlling for both auto-correlative and cross-lagged effects. Finally, regression paths from the extracted slope and intercept terms to distal outcomes are demarcated using αa-b, where "a" represents the causal variable and "b" the outcome. For visual clarity, measured variables, residual variances, and residual covariances terms for measured variables were excluded from this visualization of the model and only estimated parameters were labeled.

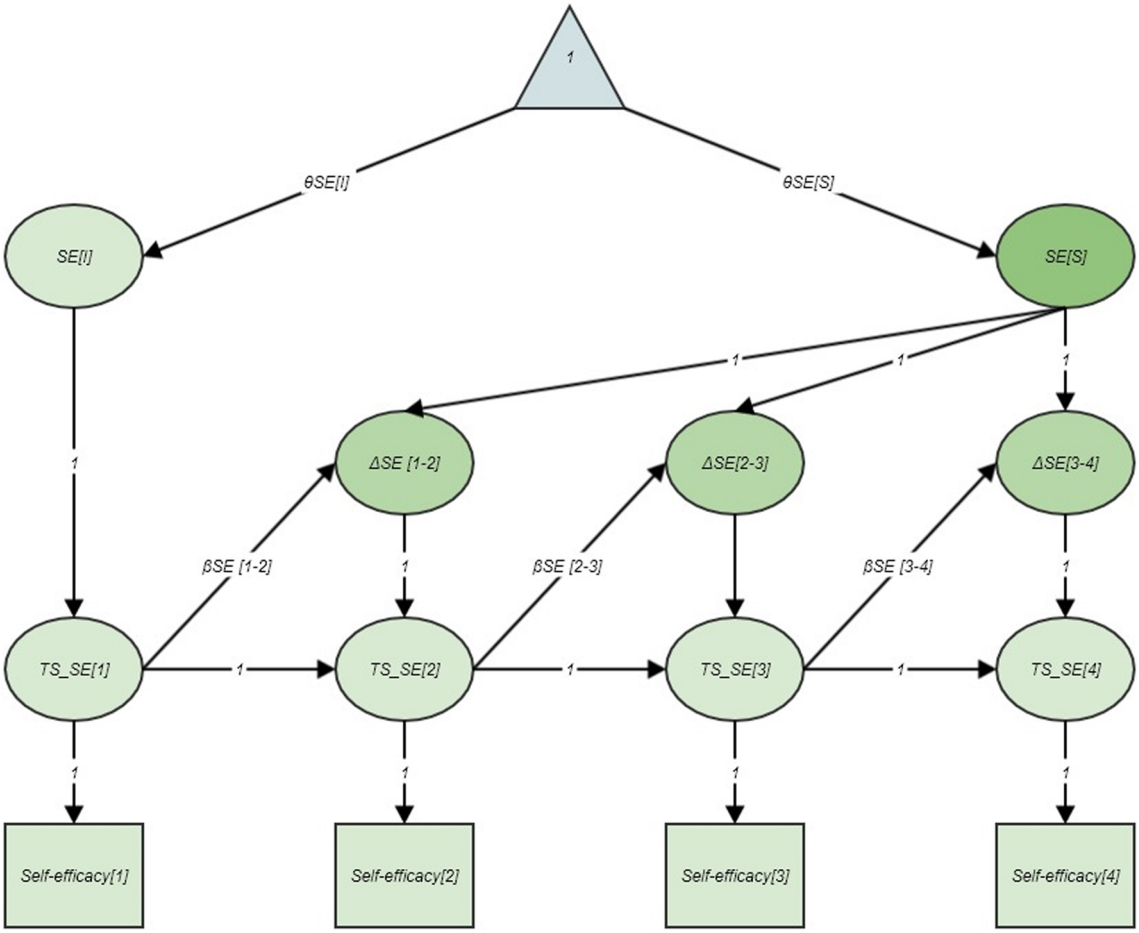

Fig. A1. Graphical representation of a univariate Dual Change Score Model for Self-efficacy where Δ*SE* represents predicted change, *βSE* represents change predicted by level at a previous time point, *θSE[I]* represents the intercept, *θSE[S]* represents the slope.

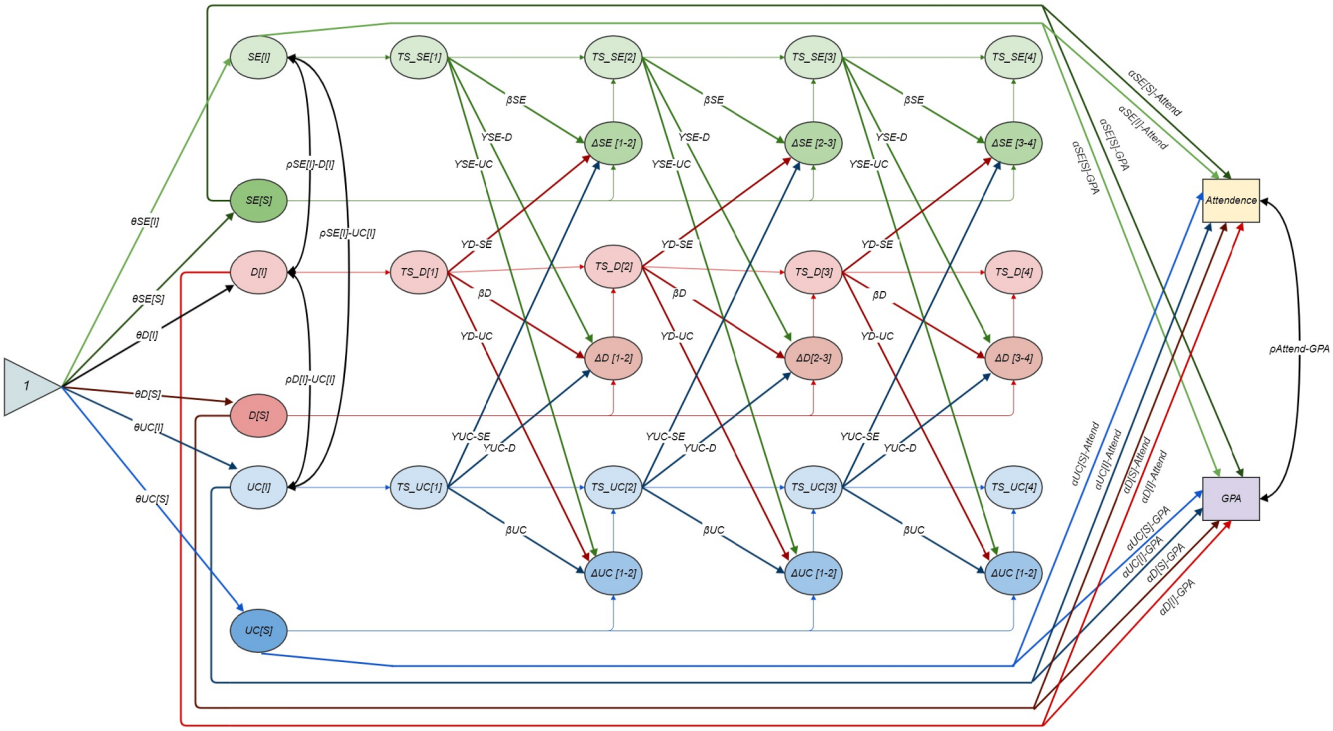

Fig. A2. Graphical representation for trivariate dual change score model, where Δfactor represents predicted change, *β* regression weights represent change predicted by level at a previous time point within variable, *ϒ* regression weights represent change predicted by level on another variable at a previous time point, θfactor[I] represents the intercept mean, θfactor[S] represents the slope mean, α regression weights represent the effect of slopes and intercepts on distal attendance and GPA outcomes, ρ represents covariances between variables.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cedpsych.2018.12.005.

References

Amitay, G., & Gumpel, T. (2015). Academic self-efficacy as a resilience factor among adjudicated girls. *International Journal of Adolescence and Youth, 20*(2), 202–227.

Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology, 44*, 427–445.

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Educational Psychologist, 42*, 223–235. https://doi.org/10.1080/00461520701621079.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Upper Saddle River, NJ: Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: Freeman & Co.

Bandura, A. (2006). Toward a Psychology of Human Agency. *Perspectives on Psychological Science, 1*(2), 164–180. https://doi.org/10.1111/j.1745-6916.2006.00011.x.

Beaujean, A. (2012). *Baylor educational psychology quantitative courses R functions and data.* Waco, TX: Baylor University.

Bouffard, T., Boileau, L., & Vezeau, C. (2001). Students' transition from elementary to high school and changes of the relationship between motivation and academic performance. *European Journal of Psychology of Education, 16*(4), 589.

Burger, K., & Samuel, R. (2017). The role of perceived stress and self-efficacy in young people's life satisfaction: A longitudinal study. *Journal of Youth and Adolescence, 46*(1), 78–90.

Burger, K., & Walk, M. (2016). Can children break the cycle of disadvantage? Structure and agency in the transmission of education across generations. *Social Psychology of Education, 19*(4), 695–713. https://doi.org/10.1007/s11218-016-9361-y.

Chen, Q., Luo, W., Palardy, G. J., Glaman, R., & McEnturff, A. (2017). The efficacy of common fit indices for enumerating classes in growth mixture models when nested data structure is ignored. *SAGE Open, 7*(1), https://doi.org/10.1177/2158244017700459.

Christenson, S. C., Reschly, A. C., & Wylie, C. (Eds.). (2012). *Handbook of research on student engagement*. New York: NY: Springer Science.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155.

Eccles, J. S. (2016). Engagement: Where to next? *Learning and Instruction, 43*, 71–75.

Eccles, J. S., & Midgley, C. (1989). Stage/environment fit: Developmentally appropriate classrooms for early adolescents. In R. Ames, & C. Ames (Vol. Eds.), *Research on motivation in education: Vol. 3*, (pp. 139–181). New York: Academic Press.

Eccles, J. S., & Roeser, R. W. (2011). Schools as developmental contexts during adolescence. *Journal of Research on Adolescence, 21*(1), 225–241.

Field, A. (2009). *Discovering statistics using SPSS.* Thousand Oaks, CA: Sage Publications.

Finn, J. D. (1989). Withdrawing from school. *Review of Educational Research, 59*, 117–142.

Finn, J. D., & Owings, J. (2006). *The adult lives of at-risk students: The roles of attainment and engagement in high school–Statistical analysis report.* United States Department of Education, National Center for Education Statistics, Institute of Educational Sciences.

Fredericks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*, 59–109.

Fredricks, J. A., & Eccles, J. S. (2002). Children's competence and value beliefs from childhood through adolescence: Growth trajectories in two male-sex-typed domains. *Developmental Psychology, 38*(4), 519.

Freedman, D. A. (2006). On the so-called "Huber sandwich estimator" and "robust standard errors". *The American Statistician, 60*(4), 299–302.

Geiser, S., & Santelices, M. V. (2007). *Validity of high school grades in predicting student success beyond the freshman year: high school record vs. standardized tests as indicators of four-year college outcomes. Research & occasional paper series: CSHE. 6.07.* Berkeley, CA: University of California Berkeley, Center for Studies in higher Education.

Ghisletta, P., & Lindenberger, U. (2005). Exploring structural dynamics within and between sensory and intellectual functioning in old and very old age: Longitudinal evidence from the Berlin aging study. *Intelligence, 33*, 555–587. https://doi.org/10.1016/j.intell.2005.07.002.

Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (2001). Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. *Journal of Educational Psychology, 93*(1), 3–13.

Graham, S. (2015). Inaugural editorial for the Journal of Educational Psychology. *Journal of Educational Psychology, 107*(1), 1–2.

Green, J., Liem, G. A. D., Martin, A. J., Colmar, S., Marsh, H. W., & McInerney, D. (2012). Academic motivation, self-concept, engagement, and performance in high school: Key processes from a longitudinal perspective. *Journal of Adolescence, 35*(5), 1111–1122.

Grimm, K., Mazza, G., & Mazzocco, M. (2016). Advances in methods for assessing longitudinal change. *Educational Psychologist, 51*(3–4), 342–353.

Hackett, G. (1995). Self-efficacy in career choice and development. In A. Bandura (Ed.). *Self-efficacy in changing societies* (pp. 232–258). New York, NY: Cambridge University Press.

Hedges, L. V., & Hedberg, E. C. (2007). Intraclass correlation values for planning group-randomized trials in education. *Educational Evaluation and Policy Analysis, 29*(1), 60–87.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.

Janosz, M., Archambault, I., Morizot, J., & Pagani, L. S. (2008). School engagement trajectories and their differential predictive relations to dropout. *Journal of social Issues, 64*(1), 21–40.

Johnson, M., Crosnoe, R., & Elder, G., Jr. (2001). Student's attachment and academic engagement: The role of Race and ethnicity. *Sociology of Education, 74*(4), 318–340.

Juvonen, J., Le, V.-N., Kaganoff, T., Augustine, C. H., & Constant, L., 2004. Focus on the wonder years: Challenges facing the American middle school. Rand Corporation.

Kass, R. E., & Wasserman, L. (1995). A reference Bayesian test for nested hypotheses and its relationship to the Schwarz criterion. *Journal of the American Statistical Association, 90*(431), 928–934.

Klem, A. M., & Connell, J. P. (2004). Relationships matter: Linking teacher support to student engagement and achievement. *Journal of School Health, 74*(7), 262–273.

Kline, R. B. (2011). *Principles and practices of structural equation modeling* (3rd ed.). New York City, NY: The Guilford Press.

Madjar, N., & Chohat, R. (2017). Will I succeed in middle school? A longitudinal analysis of self-efficacy in school transitions in relation to goal structures and engagement. *Educational Psychology, 37*(6), 680–694.

Madjar, N., & Cohen-Malayev, M. (2016). Perceived school climate across the transition from elementary to middle school. *School Psychology Quarterly, 31*(2), 270.

Marks, H. (2000). Student engagement in instructional activity: Patterns in elementary, middle, and high school years. *American Educational Research Journal, 37*(1), 153–184.

Martin, A. (2012). Part II commentary: Motivation and engagement: Conceptual, operational, and empirical clarity. In S. Christenson, A. Reschly, & C. Wylie (Eds.). *Handbook of research on student engagement.* New York, NY: Springer Science + Business Media LLC.

Martin, A. (2014). *Motivation and engagement scale Junior School: Test user manual* (14th ed.). Sydney, Australia: Lifelong Achievement Group.

Martin, A., Burns, E., & Collie, R. (2017). ADHD, personal and interpersonal agency, and achievement: Exploring links from a social cognitive theory perspective. *Contemporary Educational Psychology, 50*, 13–22.

McArdle, J. J. (2001). A latent difference score approach to longitudinal dynamic structural analysis. In r. Cudeck, S. Du Toit, & D. Sorbom (Eds.). *Structural equation modeling: Present and future* (pp. 341–380). Lincolnwood, IL: Scientific Software International.

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology, 60*, 577–605.

McMillan, J. H. (2003). Understanding and improving teachers' classroom assessment decision-making: Implications for theory and practice. *Educational Measurement: Issues and Practice, 22*(4), 34–43.

Mosher, R., & MacGowan, B. (1985). *Assessing student engagement in secondary schools: Alternative conceptions, strategies of assessing, and instruments.* University of Wisconsin, Research and Development Center (ERIC Document Reproduction Service No. ED 272812).

Muris, P. (2001). A brief questionnaire for measuring self-efficacy in youths. *Journal of Psychopathology and Behavioral Assessment, 23*(3), 145–149.

Patrick, B. C., Skinner, E. A., & Connell, J. P. (1993). What motivates children's behavior and emotion? Joint effects of perceived control and autonomy in the academic domain. *Journal of Personality and Social Psychology, 65*, 781–791.

Preacher, K. J., Wichman, A. L., Briggs, N. E., & MacCallum, R. C. (2008). *Latent growth curve modeling.* Los Angeles: Sage Publications.

Roeser, R. W., & Eccles, J. S. (1998). Adolescents' perceptions of middle school: Relation to longitudinal changes in academic and psychological adjustment. *Journal of Research on Adolescence, 8*(1), 123–158.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. <http://www.jstatsoft.org/v48/i02/>.

Skinner, E. A., Furrer, C., Marchand, G., & Kinderman, T. (2008). Engagement and disaffection in the classroom: Part of a larger motivational dynamic? *Journal of Educational Psychology, 100*, 765–781.

Thomas, M. K., Singh, P., & Klopfenstein, K. (2015). Arts education and the high school dropout problem. *Journal of Cultural Economics, 39*(4), 327–339.

Usher, E. L., & Pajares, F. (2006). Sources of academic and self-regulatory efficacy beliefs of entering middle school students. *Contemporary Educational Psychology, 31*(2), 125–141.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software, 45*(3), 1–67.

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods, 3*(1), 4–70.

Wang, M., & Eccles, J. (2012). Social support matters: Longitudinal effects of social support on three dimensions of school engagement from middle to high school. *Child Development, 83*(3) 977-895.

Wang, M. T., & Eccles, J. S. (2013). School context, achievement motivation, and academic engagement: A longitudinal study of school engagement using a multidimensional perspective. *Learning and Instruction, 28*, 12–23.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*, 548–573.

West, M., & Schwerdt, G. (2012). The middle school plunge. *Education Next, 12*(2).

Wigfield, A., Byrnes, J. P., & Eccles, J. S. (2006). Development during early and middle adolescence. In P. Alexander, & P. Winne (Eds.). *Handbook of educational psychology* (pp. 87–113). New York, NY: Routledge.

Wylie, C., & Hodgen, E. (2012). Trajectories and patterns of student engagement: Evidence from a longitudinal study. In S. Christenson, A. Reschly, & C. Wylie (Eds.). *Handbook of research on student engagement.* New York: Springer Science + Business Media LLC.

You, S., & Sharkey, J. (2009). Testing a developmental–ecological model of student engagement: A multilevel latent growth curve analysis. *Educational Psychology, 29*(6), 659–684.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology, 25*(1), 82–91.