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# Growth goals and growth mindset from a methodological-synergistic perspective: lessons learned from a quantitative correlational research program

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**ABSTRACT**

This review explores predictors and consequences of students' growth goals and growth mindset in school with particular emphasis on how correlational statistical methods can be applied to illuminate key issues and implications. Study 1 used cross-sectional data and employed structural equation modelling (SEM) to investigate the role of growth goals in mediating the link between interpersonal relationships and academic engagement. Study 2 conducted multi-group path analysis to investigate the role of growth goals in the academic outcomes of two groups of students (ADHD and non-ADHD). Study 3 used longitudinal data and SEM to test a cross-lagged panel design to investigate reciprocal links between growth goals and growth mindset. Study 4 conducted multi-level SEM where the effects of a growth orientation on engagement and achievement were investigated at the student-level (level 1) and the classroom-level (level 2). Taking these four studies together, we aim to show how correlational data and multivariate correlational analyses have been effective in answering research questions in a way that have practical and theoretical implications for students' academic growth. We also position this review as a substantive-methodological synergy – an approach recently recommended in response to concerns about the increasing polarization of substantive and methodological research and researchers.

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Growth mindset; growth goals; substantive-methodological synergies; correlational research

In a climate of accountability, benchmarks, and league tables, it is important to ensure that students are not excluded from educational 'success' or denied a sense of educational progress (Nichols and Berliner 2007; Martin 2015). Most competitive assessment systems are something of a 'zero-sum game' such that some students' success comes at the expense of other students' success (e.g. Amrein-Beardsley 2008; Nichols and Berliner 2007). Nearly 40 years ago Slavin lamented: 'some students enter class with such advanced skills that they need to do little to earn As or Bs, whereas others cannot make acceptable grades no matter how hard they try' (1980, 520). It would appear that in the past decades things are not much different, with a major review reporting 'under traditional models of assessment, some students and some schools may not experience success (because of how success is measured), regardless of how much they were learning or progressing' (Anderman et al. 2010, 128; see also Anderman et al. 2015).

Greater attention to academic growth has been suggested as one way to navigate these competitive pressures (Martin 2015). Under a growth approach to academic development, a student

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may not outperform his/her peers but can outperform their previous efforts. At the same time, although a student may demonstrate acceptable comparative achievement, there may be room for further individual growth. Indeed, according to Dweck, 'the hallmark of human nature is each person's great capacity to adapt, to change, and *to grow*' (italics added; 2012, 614; see also Dweck 2006).

In this review, our substantive focus is on academic growth goals and academic growth mindset. We have empirically attended to both constructs through a research programme exploring predictors and consequences of students' growth goals and growth mindsets in high school. We describe how our different data sources and data types have been analyzed to answer core questions around students' growth approaches to school and schoolwork. Drawing on cross-sectional and longitudinal data, we have employed correlational analyses (viz. path analysis, structural equation modelling, multilevel modelling) to answer our research questions. As we seek to demonstrate, correlational designs are inherently flexible and allow different insights into a core construct. In so doing, correlational designs have the significant capacity to advance research and understanding about a target construct – in this review, academic growth.

## Growth goals and growth mindset

Individuals develop theories, beliefs, and deeply held schema about human attributes that help them to understand and explain their world (Dweck 2000, 2006; Martin et al. 2016). Implicit theories of intelligence (sometimes also referred to as implicit beliefs about intelligence) refer to an individual's beliefs about the malleability of intelligence. Individuals can hold a fixed and immutable view of intelligence (i.e. an entity theory, or entity belief). Or, they can hold a view that intelligence can be changed or improved upon with effort (i.e. an incremental theory, or incremental belief; Dweck 2000, 2006). Recently, a more popularized terminology has been used that reflects the 'growth' dynamic (i.e. 'growth mindset') underpinning this theoretical framework. A growth mindset refers to an individual's belief that intelligence (and related attributes) can be developed through appropriate investment of effort (Dweck 2006; Martin 2015). There has been much research into individuals' growth mindset across domains as diverse as education, business, sport, the creative and performing arts, and parenting (see Dweck 2006 for reviews). In general, those holding a growth mindset tend to have better academic and personal wellbeing outcomes (Dweck 2006; Tarbetsky, Collie, and Martin 2016). Herein, we focus on the education (school) domain as a means to describe and explain a growth mindset and outline recent studies that explore the role of a growth mindset in students' academic outcomes.

Alongside a student's growth mindset, research has also explored growth goals. Growth goals are specific, challenging, and competitively self-referenced goals aimed at self-improvement (Martin and Elliot 2016a, 2016b). There are process growth goals (e.g. studying longer this week than last week) and outcome growth goals (e.g. improving on one's prior test score). In general, students who set growth goals tend to have better academic outcomes (Martin 2015).

## A correlational research programme investigating growth

In this discussion, we draw on four of our published correlational studies that have harnessed different methodological and analytical approaches to better understand growth mindsets and growth goals in students' academic lives. In Study 1 we used cross-sectional data and employed structural equation modelling (SEM) to investigate the role of growth goals in mediating the link between interpersonal relationships and academic engagement (Collie et al. 2016). Study 2 conducted multi-group path analysis to investigate the role of growth goals in the academic outcomes (engagement and achievement) of two groups of students (ADHD and non-ADHD; Martin 2012; see also Martin 2013). Study 3 employed longitudinal data and SEM to test a cross-lagged panel design to investigate reciprocal links between growth goals and growth mindset (Martin 2015). In Study 4 we conducted multilevel SEM where the effects of an overarching growth orientation (comprising growth goals and growth mindset) on engagement and achievement were investigated at the student- (level 1) and classroom-level (level 2; Bostwick et al. 2017; Bostwick et al. 2017). Taking these four studies together, we aim to show how correlational data and analysis are integral to answering research questions with practical and theoretical implications.

## Substantive-methodological synergy

There are two strands to this review. The first attends to the substantive issues of growth goals and growth mindset. It synthesizes findings from a programme of research that addresses conceptual and applied implications of these growth-oriented constructs. In addition to these substantive issues, there is a methodological purpose to the present review. Specifically, it provides an opportunity to explore various analytical means of examining growth constructs and thereby consider methodological elements relevant to this line of research. The review is, then, a demonstration of substantive-methodological synergy in the educational domain. There has been concern about the gap between cutting-edge substantive and methodological research and the threat of increasing polarization of substantive and methodological research and researchers (Marsh and Hau 2007). There is also recognition that some of the best methodological research comprises creative solutions to substantive issues and that robust substantive research is founded on strong and sometimes creative methodologies (Marsh and Hau 2007). The present review is one attempt to synthesize substantive and methodological foci to address important educational issues as relevant to students' academic growth.

## Study 1: cross-sectional structural equation modelling of growth goals

Early research into growth goals identified its association with various educational 'outcomes', including class participation, enjoyment of school, and educational aspirations (Martin 2006). Following these initial promising findings there was a need to understand growth goals in the context of students' educational ecology. In line with major psycho-educational theorizing that emphasizes students' interpersonal contexts in shaping their motivation (Furrer and Skinner 2003; Deci and Ryan 2012; Martin and Dowson 2009; Wentzel 2010), one channel of research considered how students' interpersonal relationships were linked to students' growth goals and where this relationship sat within the broader motivation and engagement process. Accordingly, Collie et al. (2016) examined the role of growth goals in mediating the association between interpersonal relationships and academic outcomes. Specifically, they examined the extent to which students' relationships with teachers, parents, and peers are associated with growth goals and the extent to which growth goals (beyond the effects of interpersonal relationships) were associated with cognitive, behavioural, and emotional engagement at school.

### *Methodological elements*

The sample comprised 3,232 school students in junior high (11-15 years; 50%) and senior high (16-19 years; 50%) from 12 schools in major cities in the US, Canada, and the UK. The dataset was cross-sectional; that is, all data were collected in a survey at one time. We assessed three interpersonal relationship factors: teacher relationships (e.g. 'In general, my teachers really listen to what I have to say'; 4 items), parent relationships (e.g. 'My parents understand me'; 4 items), and peer relationships (e.g. 'Overall, I get along well with other students at this school'; 4 items). We assessed growth goals (e.g. 'When I do my schoolwork I try to do it better than I've done before') using 4 items. We measured three types of engagement: cognitive engagement (via academic intentions, e.g. 'I intend to complete school'; 4 items), behavioural engagement (via class participation, e.g. 'I get involved in things we do in class'; 4 items), and emotional engagement (via school enjoyment, e.g. 'I like school'; 4 items). Data were also collected on socio-demographic characteristics including sex, age, grade, language background, parent education, parent occupation, and prior achievement. Including these in the model (as covariates) meant we could account for their influence and thus better understand the unique effects of interpersonal relationships, growth goals, and engagement (i.e. beyond variance attributable to background factors).

We used SEM to analyze our data. SEM comprises two parts: a measurement and a structural part (see Byrne 2012 for a summary). Figure 1 shows these two parts. The measurement part estimates each latent factor from the collection of items in the survey used to assess it (see measurement part of Figure 1). For example, the four growth goal items are used to estimate the latent growth goal factor. The structural part of SEM links the latent factors in a directional and ordered way according to hypotheses (see Figure 1 for structural part).

Building on the basic model shown in Figure 1, we used SEM to assess the associations among interpersonal relationships, growth goals, and engagement. As seen in Figure 2, each of the substantive factors in the model (i.e. relationships, growth goals, and engagement) were estimated by their component items (measurement part) and then each factor was linked through a series of regression equations (structural part). This model can be tested in a one-step (simultaneous) analysis and goodness-of-fit indices can be assessed to determine if the model fits the data (for summaries see McDonald and Marsh 1990; Schumacker and Lomax 2010). SEM is conducted using specialized software – in our case, with M*plus* (Muthén and Muthén 2017).

The results generated inform whether, to what extent, and in what direction each factor is linked to another. Thus, for example, the results inform the strength and direction (positive or negative) of the following links in the model: interpersonal relationships → growth goals, growth goals → academic engagement, and interpersonal relationships → academic engagement (Figure 2). As with regression analysis, each of these structural relationships is represented by standardized beta weights (β) that are accompanied by a significance (*p*) value. In addition, because this is a mediation model, SEM allows us to formally explore the indirect effect of interpersonal relationships on academic engagement via growth goals. With appropriate syntax, M*plus* can generate standardized indirect effects to provide information on the mediating role of growth goals.

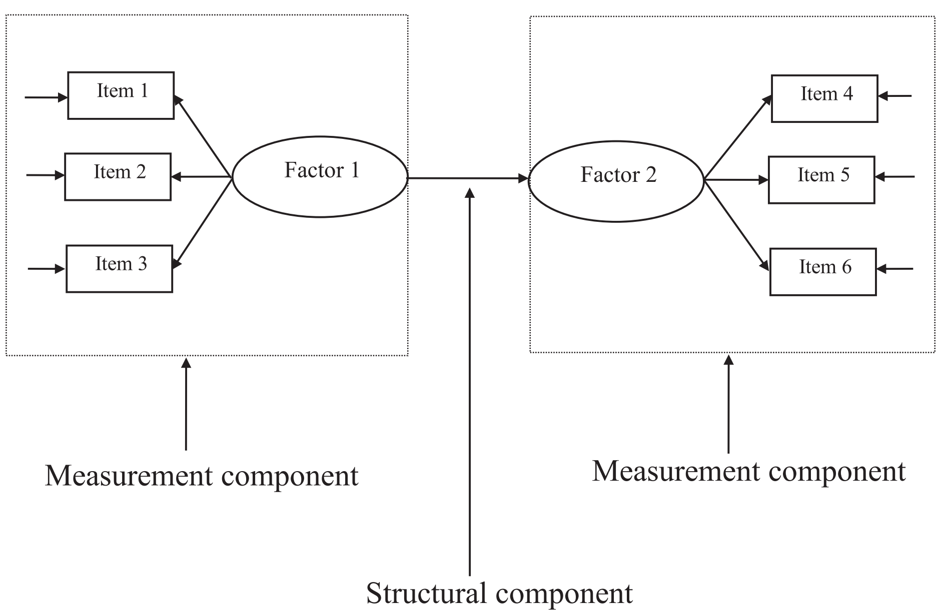


**Figure 1.** Measurement and structural components of a structural equation model.

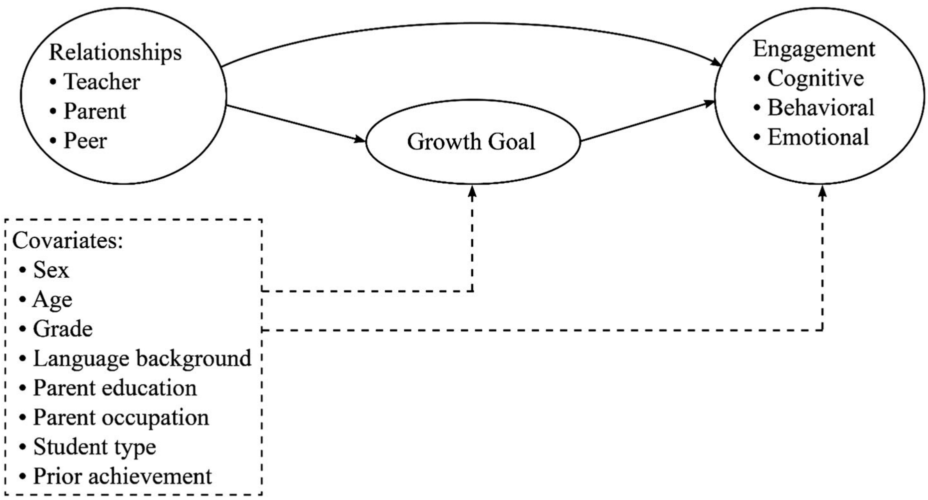


**Figure 2.** Study 1 – Hypothesized model of interpersonal relationships, growth goals, and engagement (controlling for socio-demographic and achievement covariates). Growth goals play a mediating role between interpersonal relationships and academic engagement. Dashed lines indicate covariate paths that are estimated, but which are not central to substantive research question.

### *Substantive findings and methodological next steps*

The results from the SEM showed that quality relationships were significantly and positively associated with growth goals. In turn, growth goals significantly and positively predicted academic engagement. That is, more positive relationships with teachers, parents, and peers predicted the pursuit of growth goals and students who pursued growth goals reported higher academic engagement. Thus, these results provided a new understanding of the relative salience of associations among interpersonal relationships, growth goals, and academic engagement – and in particular, one of the mechanisms (growth goals) by which interpersonal relationships may impact academic engagement.

This cross-sectional SEM entailed investigating the predictors (interpersonal relationships) and consequences (academic engagement) of growth goals. A further basis upon which to interpret SEM findings is to ascertain if the predictive effects are the same for different groups of students. This allows a test of the generalizability of the hypothesized process – for example, the role of growth goals for one group of students (e.g. boys, elementary school students, low SES, non-English-speaking background students, etc.) compared to the role of growth goals for another group of students (e.g. girls, middle school students, high SES, English-speaking background students, etc.). If we find growth goals operate in much the same way for the different groups, then we can suggest that the effects of growth goals generalize across students. However, if we find that growth goal effects are different across groups, then we get to better understand these groups (and the distinct ways they function) and the growth goal construct itself. Indeed, this information also serves as a critical point for intervention; for example, if growth goals are influential for one group but not another, it identifies a group that practitioners might target to enhance academic outcomes. Accordingly, Study 2 used multi-group path analysis to compare the role of growth goals in the academic outcomes of students with ADHD and their non-ADHD peers (Martin 2012).

### *Study 2: multi-group path analysis of growth goals*

Growth goals have been shown to benefit academic outcomes in studies of 'general' samples (i.e. undifferentiated by academically at-risk sub-groups within them) of school students (e.g. Burns, Martin, and Collie 2017; Martin 2006; Martin and Liem 2010). However, if growth goals are to be implemented in 'general' classrooms, it is important to demonstrate the generalizability of positive effects across a diversity of students in those classrooms. Accordingly, recent research explored the role of growth goals among two groups of students: those with ADHD and their non-ADHD peers residing in the same schools (Martin 2012; see also Martin 2013).

In the DSM-5, ADHD is defined as 'a persistent pattern of inattention and/or hyperactivity-impulsivity that interferes with functioning or development' (American Psychiatric Association 2013, 59). It is estimated that 3%–5% of children are diagnosed with ADHD (Purdie, Hattie, and Carroll 2002), but population estimates put this higher at around 10% (Woodruff et al. 2004). The academic problems that follow from ADHD are well documented. Students with ADHD face increased risk of poor achievement, school exclusion, schoolwork non-completion, school refusal, grade repetition, and changing classrooms and/or schools (see Barkley 2006; Martin 2014; Purdie, Hattie, and Carroll 2002 for reviews). Because growth goals have been shown to enhance academic outcomes, it was of interest to determine growth goal effects for a sample of students with ADHD, compared to their non-ADHD peers. Because students with ADHD demonstrate significantly poorer academic outcomes than their non-ADHD peers (Barkley 2006; Purdie, Hattie, and Carroll 2002), we were especially interested if growth goals may have particular yield for students with ADHD (and thereby have merit as a strategy to reduce the achievement gap between the two groups).

Multi-group analyses are useful for addressing this issue: in the model, the association between growth goals and various academic outcomes can be explored for ADHD and non-ADHD groups. In so doing, we can ascertain the role of growth goals for each group and formally test whether growth goal effects for one group (e.g. students with ADHD) are significantly higher or lower than growth goal effects for the other group (students without ADHD). In Study 2, the academic outcomes of interest were achievement, homework completion, persistence, planning and monitoring, task management, self-handicapping, and disengagement. We were interested in the extent to which growth goals predicted these outcomes for ADHD and non-ADHD groups (see Figure 3(a,b)).

### *Methodological elements*

The ADHD sample comprised 87 students in junior high school 11-14 years (61%) and senior high school 15-19 years (39%) from nine 'general' Australian schools. The non-ADHD sample comprised a large $N = 3374$ cohort from the same schools and year levels as the students with ADHD. Growth goals were assessed with four items (e.g. 'When I do my schoolwork I try to do it better than I've done before'). Other variables were planning (e.g. 'Before I start an assignment I plan out how I am going to do it'; 4 items), task (study) management (e.g. 'When I study, I usually study in places where I can concentrate'; 4 items), persistence (e.g. 'If I can't understand my schoolwork at first, I keep going over it until I do'; 4 items), self-handicapping (e.g. 'I sometimes don't study very hard before exams so I have an excuse if I don't do so well'; 4 items), disengagement (e.g. 'I've pretty much given up being involved in things at school'; 4 items), and homework completion ('How often do you do and complete your homework?'; 1 item). Academic achievement was based on students' results in annual nation-wide assessment of literacy and numeracy (National Assessment Program in Literacy and Numeracy, NAPLAN) administered by the Australian Curriculum and Assessment and Reporting Authority (ACARA). As covariates, data were also collected on personality as well as socio-demographic characteristics including: sex, age, language background, socio-economic status (SES), parent education, and parent occupation. Including these in the model meant we could account for their influence and thus better understand the unique effects of growth goals on the academic outcomes for ADHD and non-ADHD groups (i.e. beyond variance attributable to background factors).

Data analysis involved multi-group (ADHD, non-ADHD) multivariate (multiple independent/covariate and dependent variables) path analysis using M*plus* (Muthén and Muthén 2017). Here, for each group, the growth goal factor was entered alongside the covariates as a predictor of the seven academic outcome factors. Figure 3(a) (the ADHD part of the path analysis) and Figure 3(b) (the non-ADHD part of the path analysis) demonstrate the full model. The advantage of multi-group analyses

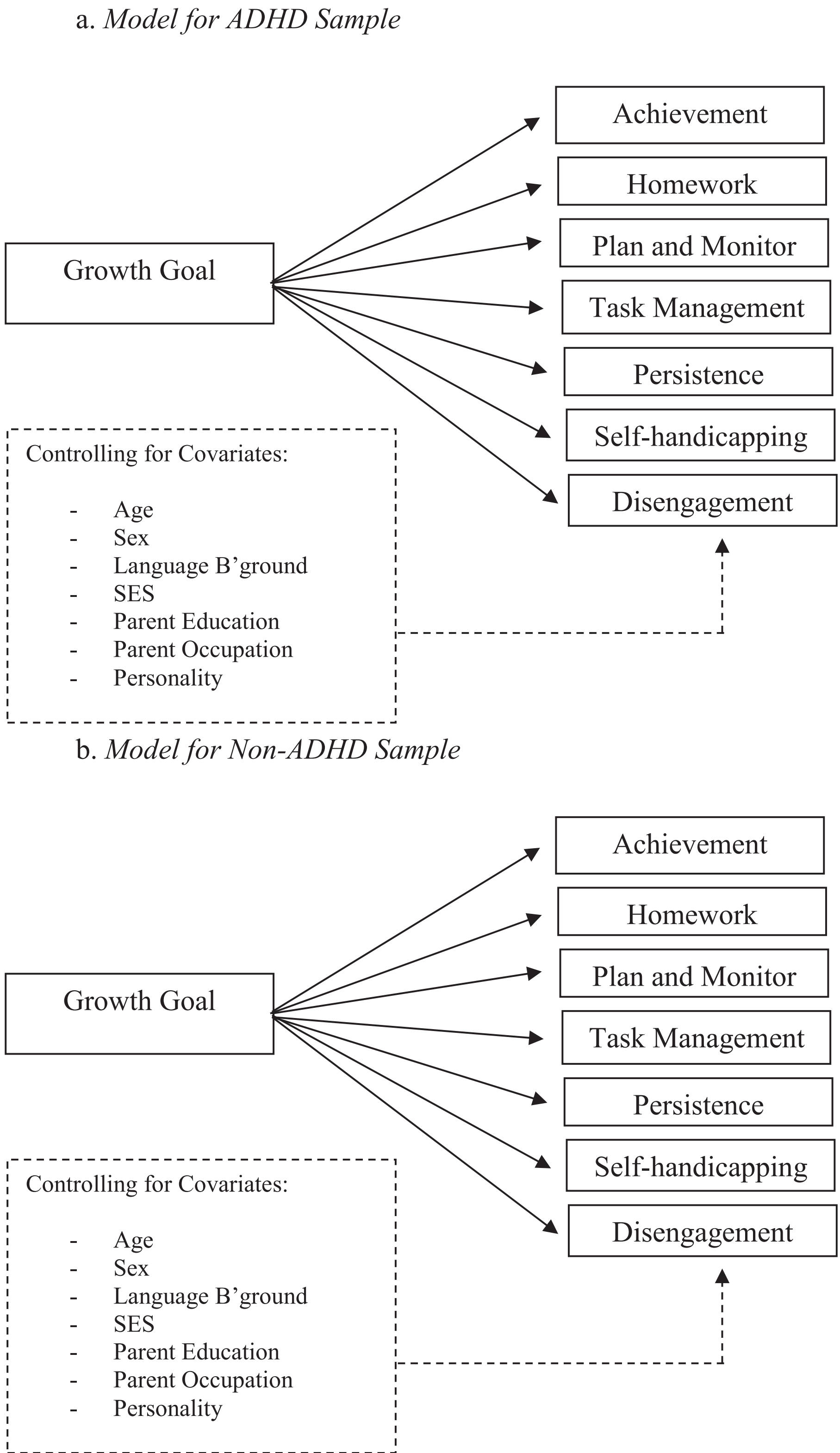


**Figure 3.** Study 2 – Multi-group Path Analysis: Growth goals predicting academic outcomes (controlling for socio-demographic and personality covariates) for a group of students with ADHD and a group of their non-ADHD peers. Dashed lines indicate covariate paths that are estimated, but which are not central to substantive research question.

is that parameters (standardized beta coefficients) between the two groups can be compared to determine if one group differs from the other.

### Substantive findings and methodological next steps

Multi-group, multivariate path analysis demonstrated that there were (a) significant and positive associations between growth goals and academic outcomes for students with ADHD (Figure 3(a, b)) similar positive effects for non-ADHD students (Figure 3(b)). We can therefore say that the positive effects of growth goals generalize across students with ADHD and their non-ADHD peers. However, notwithstanding this generality, there was a key distinction important to consider. Specifically, growth goals yielded a stronger relationship to outcomes for students with ADHD (in 5 out of the 7 outcome measures) than for students who did not have ADHD. This has significant practical implications because it suggests that promoting growth goals for students with ADHD may evince greater gains on achievement and engagement measures relative to non-ADHD peers. Furthermore, this suggests that the promotion of growth goals may be one means to reduce the achievement gap between students with ADHD and their non-ADHD peers.

Having established several predictors and consequences of growth goals in Study 1 and 2, and explored the generality of growth goals across students at academic risk and not at academic risk (Study 2), we were interested in extending this cross-sectional research by collecting longitudinal data. Because cross-sectional data are collected at one time point, the hypothesized directional relationships among the factors (see Figures 2 and 3(a,b)) are based primarily on theoretical grounds. A more powerful basis upon which to conduct analyses is to collect longitudinal data. This allows a more robust test of the ordering of factors – for example, the role of growth goals in one year (or semester, term, etc.) predicting outcomes in the next year (or semester, term, etc.). Longitudinal methodology also allows us to move closer to understanding factors that further explain how a construct may operate and thereby serve as direction for intervention (Martin 2011). That is, to the extent that a factor (e.g. growth goal) at 'time 1' is a significant predictor of outcomes at 'time 2', it (growth goal) becomes a potential factor that practitioners might target to enhance outcomes in a student's academic life. Accordingly, Study 3 used longitudinal data and SEM to conduct a cross-lagged panel design to investigate reciprocal links between growth goals and growth mindset.

### Study 3: longitudinal SEM of growth goals and growth mindset

As indicated earlier, growth mindset has received a great deal of attention in recent years and has been found to be associated with academic and personal wellbeing (Dweck 2000, 2006). From a practitioner's perspective, then, there is a need for research to investigate ways to promote a growth mindset among students. A recent longitudinal study investigated the role of growth goals as a means to boost a growth mindset (Martin 2015). In this research, data were collected on growth goals and growth mindset in one academic year (time 1) and again a year later (time 2) from the same students (Figure 4).

Collecting data on all constructs at times 1 and 2 enables quite a powerful research design: a cross-lagged panel design (Martin and Liem 2010). Here, we can ask whether one of the two constructs is 'directionally' salient over time (i.e. one construct predicts the other), whether there exists a reciprocal relationship over time (i.e. both constructs predict each other), or whether there is no relationship over time. Thus, answers to three questions were sought: (a) are prior growth goals a significant predictor of later growth mindset, (b) is prior growth mindset a significant predictor of later growth goals, or (c) are prior growth goals and growth mindset both significant predictors of later growth mindset and growth goals respectively? Essentially, then, this design allows us to understand the directional salience of growth goals and growth mindset over time. The extent to which one is salient over the other, or to the extent that they are reciprocally related, holds implications for psycho-educational interventions aimed at promoting growth mindsets and growth goals.

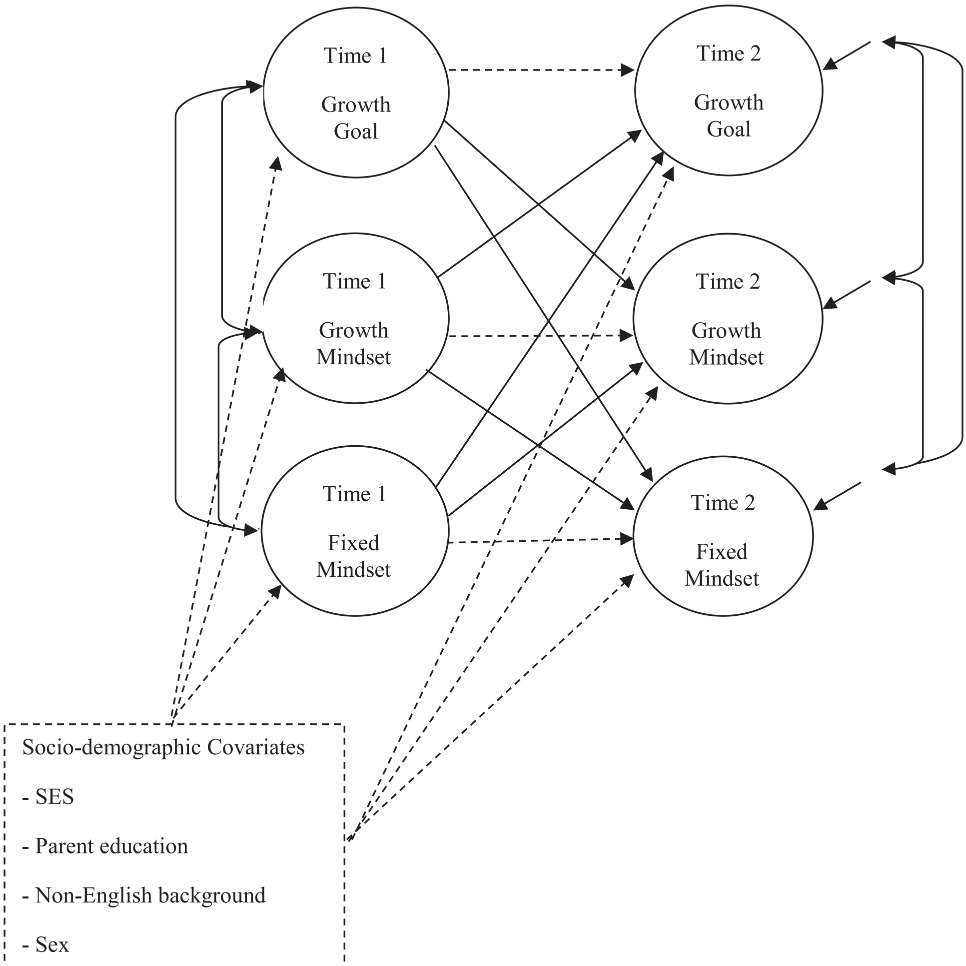


**Figure 4.** Study 3 – Longitudinal (Cross-lag) Model of Growth Goals and Growth Mindset (controlling for socio-demographic covariates): Key 'cross-lag' parameters involve time 1 growth goals and growth mindset predicting time 2 growth mindset and growth goals (respectively). 'Auto-regression' parameters involve time 1 growth goals and growth mindset predicting time 2 growth goals and growth mindset (respectively). Dashed lines indicate paths estimated that are not central to substantive research questions: (a) autoregression (test-retest) paths between time 1 and time 2 goal and mindset factors and (b) paths between covariates and substantive factors.

### *Methodological elements*

A total of 969 high school students participated from junior high, aged 11-14 years (54%) and senior high, aged 15-19 years (46%). Students were from nine high schools in four major urban areas of Australia. This dataset was longitudinal in that data were collected in a survey in one year and then students were re-surveyed one year later. We assessed growth goals via four items (e.g. 'When I do my schoolwork I try to do it better than I've done before'). We assessed growth mindset via its two salient factors: fixed (or entity) beliefs and growth (or incremental) beliefs. Fixed beliefs were assessed via five items (e.g. 'People can learn new things but how smart they are doesn't change'). Growth beliefs were also assessed with five items (e.g. 'Any person could get smarter if they worked hard'). As covariates, data were also collected on socio-demographic and other characteristics including: sex, age, language background, parent education, socio-economic status (SES), and ability. Including these in the model meant we could account for their influence and thus better understand the unique effects of growth goals and growth mindset (i.e. beyond variance attributable to background factors).

The model analyzed is shown in Figure 4. Here it can be seen that time 1 growth goals are hypothesized to predict time 2 growth mindset and time 1 growth mindset predicts time 2 growth goals. It is also noted that time 1 growth goals predict time 2 growth goals and time 1 growth mindset predicts time 2 growth mindset. The latter two parameters are referred to as 'auto-regression' and are a powerful inclusion in longitudinal modelling (representing a major advantage over cross-sectional analysis that is not able to model auto-regression). Including auto-regression means, for example, any predictive role of time 1 growth goals on time 2 growth mindset is above and beyond the influence of prior (time 1) growth mindset. For practitioners this is especially important because it means that efforts to promote growth goals will have effects on later growth mindset beyond any existing levels of growth mindset a student may have.

These analyses used M*plus* (Muthén and Muthén 2017) and employed a 'cross-lagged panel design', a technique used to disentangle and differentiate the strength of competing 'directional' interpretations between factors assessed on two different occasions (Martin 2011; Martin and Liem 2010). SEM represented growth goals and growth mindset (operationalized as two factors: fixed mindset and growth mindset) as latent factors purged of unreliability.

### *Substantive findings and methodological next steps*

Findings showed that time 1 growth goals predicted time 2 growth mindset (positively) and time 2 fixed mindset (negatively), as well as predicted time 2 growth goals. Notably, however, time 1 growth mindset and time 1 fixed mindset did not predict growth goals at time 2. Interestingly, a fixed mindset at time 1 negatively predicted growth mindset at time 2 (but positively predicted time 2 fixed mindset) and a growth mindset at time 1 negatively predicted a fixed mindset at time 2 (but positively predicted time 2 growth mindset). Taken together, these findings suggest that fixed and growth mindsets are directionally related across time – because at time 1, each predicts the other at time 2; but that growth goals are directionally salient over fixed and growth mindsets – because at time 1, growth goals predict time 2 mindsets, whereas time 1 mindsets do not predict time 2 growth goals.

The longitudinal cross-lagged nature of our data and modelling enabled us to explore the 'causal' ordering of growth goals and growth mindset. Essentially, these findings suggested that growth goals are a means of promoting a growth mindset (and reducing a fixed mindset), but mindset is not necessarily a means of promoting subsequent growth goals. Underpinning these findings was a distinct and powerful research design. For example, Studies 1 and 2 involved cross-sectional data and we could only examine associations at one point in time. Given that Studies 1 and 2 had no prior data, we could not determine if one factor (e.g. growth goals) predicted an outcome factor (engagement) beyond any prior engagement the student may possess. However, with longitudinal data we were able to control for prior variance in an outcome factor and thus better understand the salience of one factor over another across time. To the extent that a growth factor (e.g. growth goal at time 1) predicts an outcome (e.g. growth mindset at time 2) beyond prior variance in that outcome (growth mindset at time 1), we can say that educational intervention focusing on growth goals is likely to lead to notable changes in subsequent growth mindset. Importantly, this conclusion is only possible when longitudinal data are collected and when appropriate modelling is conducted (e.g. cross-lagged panel analyses). This is a good example of where methodology has direct implications for advice on intervention.

Building on Study 3, there is an adaptation of methodology that has additional implications for educational intervention. Studies 1, 2, and 3 were conducted at the student level, without regard for the classrooms to which students belong. Education is a classic domain in which there exists naturally hierarchically structured data, with students nested within classes (for example). When individuals are grouped, their group becomes potentially differentiated from other groups, and its members and the group itself both influence and are influenced by the group membership (Goldstein 2003; Muthén and Muthén 2017; Raudenbush and Bryk 2002). Thus, for example, in addition to examining whether a growth construct leads to a positive academic outcome, we can also ask whether said growth construct at the classroom level may lead to positive classroom outcomes. Or, put another way, in addition to a student-level growth factor predicting student-level academic outcomes, does a class-average growth factor predict class-average outcomes? The most appropriate technique for answering this question is multilevel modelling (or, hierarchical linear modelling).

### *Study 4: multilevel modelling of growth orientation*

Multilevel modelling (or, hierarchical linear modelling) is a statistical technique that models both individual- and group-level data. This has important implications for both theory and practice. Many theories of human development incorporate individual and group processes, emphasizing that individuals and the groups to which they belong are not independent and that both impact development (e.g. Bronfenbrenner 2001; Sameroff 2009; Shonkoff and Phillips 2000). Alongside the theoretical reasons for analyzing both individual- and group-level data, there are also statistical reasons to do so. For example, there are biases associated with single-group and single-level approaches and multilevel modelling seeks to resolve these biases including, inter alia: units/levels of analysis; dependencies within groups; and confounding of within- and between-group variables (for discussions see Goldstein 2003; Hox 2010; O'Connell and McCoach 2008; Raudenbush and Bryk 2002). The multilevel approach offers a more appropriate means of evaluating hierarchical data than would be possible with traditional single-level approaches that ignore the clustering of individuals within groups.

In Study 4, we collected mathematics-specific growth orientation data (comprising growth mindset, self-based growth goals, and task-based growth goals) from students (Bostwick, Collie et al. 2017; Bostwick, Martin et al. 2017). We also coded students according to what class they belonged to – enabling us to also analyze data at the classroom level. Thus, students (level 1) were nested within classrooms (level 2). Whereas literature on students' growth constructs continues to identify important components of these growth constructs in students, relatively few studies have addressed the influence of group-level processes relevant to growth constructs and academic outcomes. We thus expanded student-level research into academic growth by also examining the predictive utility of class-average growth orientation on class-average engagement and achievement. Figure 5 demonstrates the predictive relationships.

### *Methodological elements*

Students ($N = 1414$) in grades 7 through 9 from 19 secondary schools across three states in Australia participated in the study. The student survey consisted of mathematics-specific measures. Multilevel modelling represented each substantive variable at student-level (level 1) and class-average level (level 2). Growth orientation was assessed via growth mindset (e.g. 'Anyone can always substantially change how good they are in maths'; 2 items), self-based growth goals ('In maths, I am mainly focused on self-development and reaching my personal best'; 1 item), and task-based growth goals ('In maths, I am mainly focused on learning and understanding'; 1 item). These indicators were used to estimate a global latent growth orientation factor. Engagement was assessed via behavioural ('I get involved in things we do in maths'), emotional ('I enjoy maths'), and cognitive ('I look forward to continuing with maths in school and beyond') measures. Achievement was assessed through a 10-item mathematics test that began with arithmetic and progressed to basic calculus (presented in a multiple-choice response format and later converted to a dichotomous scoring system; correct vs. incorrect – that could be summed to form a total score). In order to ascertain the unique influence of students' growth orientation on academic outcomes, we used five control variables: grade, sex, language background, socio-economic status (SES), and prior numeracy.

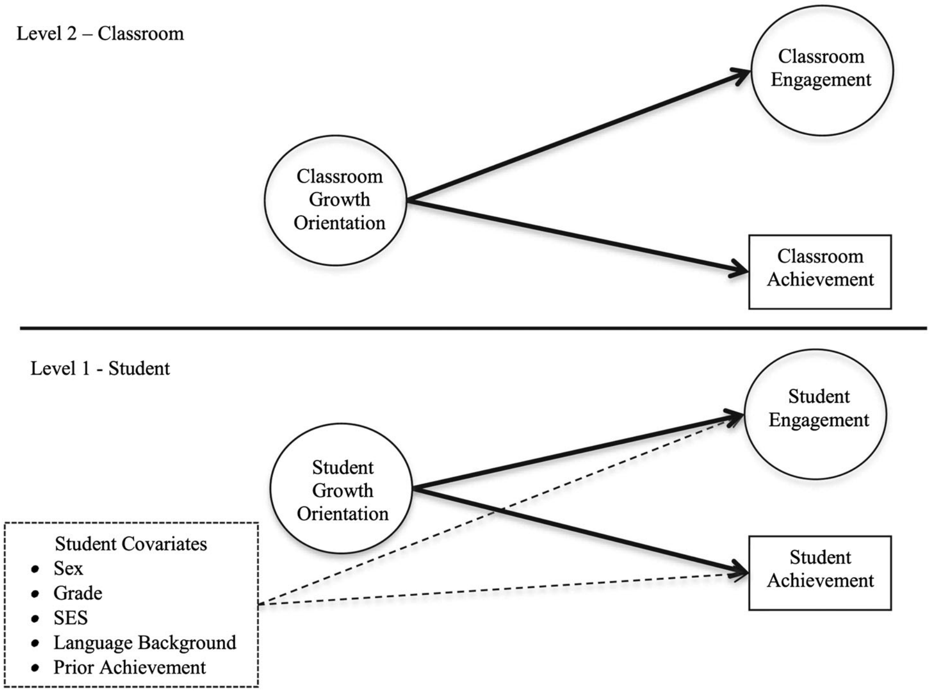


**Figure 5.** Study 4 – Multilevel Structural Equation Model (controlling for socio-demographic covariates): Growth orientation at student (level 1) and class (level 2) levels predicting student-level (level 1) and class-average (level 2) academic engagement and academic achievement. Dashed lines indicate covariate paths that are estimated, but which are not central to substantive research question.

Multilevel structural equation model with M*plus* (Muthén and Muthén 2017) was used to test the influence of class-average growth orientation on class-average engagement and achievement, controlling for the influence of covariates. As demonstrated through Figure 5, the multilevel model examined relationships among the substantive constructs at both the individual student level (level 1) and the aggregate classroom level (level 2).

### *Substantive findings and methodological implications*

At level 1, results showed that students' growth orientation predicted their engagement and achievement after controlling for shared variance in the academic outcomes and the influence of covariates. Notably, at level 2, classroom growth orientation predicted classroom engagement and classroom achievement. This has significant implications for educational practice. Most research to date had suggested the importance of student-level intervention for promoting growth orientation (e.g. targeting individual students' self-beliefs and approaches to self-improvement). Using multilevel data and multilevel modelling, this study demonstrated that whole-class intervention may also be advisable. Thus, beyond individualized approaches to promoting growth, pedagogical approaches to growth mindset and growth goals at the classroom-level are also important. The findings also have implications for theory. For example, growth goal and growth mindset concepts have predominantly centred on the individual and intra-psychic orientations to school, work, etc. Study 4 findings suggest that theory ought also recognize the presence and role of these constructs at group and organizational levels. Once more, it was the nature of the data (hierarchical) and the nature of the analytic approach (multilevel modelling) that led to practical directions and theoretical implications for students' growth orientations and their academic development.

## General discussion and conclusions

### *Further considerations emanating from different correlational designs*

Our review has sought to provide further understanding about various correlational approaches that can be employed to empirically explore growth constructs. We showed how different methodological and analytical approaches are able to answer different research questions and help us better understand different aspects of growth mindset and growth goals in students' academic lives. For example, SEM identified growth goals as a mediator in the academic process, multi-group path analysis showed different roles of growth goals for distinct groups of students (ADHD and non-ADHD), cross-lagged panel SEM shed light on directional links between growth goals and growth mindset, and multi-level SEM identified student-level (level 1) and classroom-level (level 2) effects for growth goals and growth mindset. In addition to the substantive insights around growth that these studies provide, there are methodological insights into how correlational data and multivariate correlational analyses have practical and theoretical implications for students' academic growth. Here we briefly discuss some salient and indicative implications as relevant to each study.

Study 1: These cross-sectional correlational analyses revealed that PB goals played an important role in how teacher and peer relationships were associated with academic outcomes. Cross-sectional correlational analyses provided preliminary evidence for the relationships that may exist among constructs and help to lay the foundation for future avenues of research. In explaining these connections, we turned to the self-determined quality of PB goals (Collie et al. 2016). Specifically, in that paper we contended that PB goals were related with positive academic outcomes because schoolwork is seen by students as more relevant when they are working on goals chosen by, about, and for themselves. Importantly, these factors are shown to be aligned with self-determination (Deci and Ryan 2012). We further suggested that if goals are not created by the students themselves or are done so based on the teacher's ideals, this may not be as self-determined. Accordingly, we recommended that future research examines how these different motives might influence the outcomes of PB goals.

Study 2: The findings from this multi-group correlational design showed that the positive role of PB goals generalizes from non-ADHD students to students at academic risk (e.g. students with ADHD) (Martin 2012). Multi-group correlational designs address questions about how and if constructs may function differently across important groups of students; these analyses can address if the benefits or consequences of constructs are experienced similarly across groups. This is noteworthy from an inclusion perspective: the fact that the same goal approach may be beneficially implemented across ADHD and non-ADHD students in the one classroom allows for efficiencies and greater inclusiveness in pedagogical strategies. It also provides an evidential basis for optimism for the many students who typically struggle in their academic pathways (in the case of Study 2, students with ADHD). Needed now is an understanding of why students with ADHD benefit under PB goals (and in some cases, more so than students without ADHD based on differences in correlational parameters – see Martin 2012). This is an area for future research.

Study 3: Results from this longitudinal cross-lagged correlation design suggested directional salience of PB goals over students' growth or fixed mindset. Cross-lagged models seek to address 'chicken-egg' questions, allowing theorists to move beyond uni-directional or static self-system models to more appropriately recognize the dynamic interaction among factors in human functioning (Marsh 2007; Marsh and Craven 2006). Study 3 findings lent some clarification to the nature of the relationships between growth goals and a growth mindset. There has been wide agreement on the connection between implicit theories and goals (e.g. Burnette et al. 2013; Dweck 2006). However, there was a need to better understand the precise nature of their connections. Our correlational modelling across time under a cross-lagged SEM design made this possible. This now leaves open the question of how individuals coordinate growth goals and growth mindset in practice. Further research to understand and disentangle this would be useful.

Study 4: In Study 4 we conducted a multi-level SEM where the effects of an overarching growth orientation (comprising growth goals and growth mindset) on engagement and achievement were investigated at the student (level 1) and classroom level (level 2; Bostwick, Collie et al. 2017; Bostwick, Martin et al. 2017). Multilevel SEM enables investigations that seek to address if environmental or contextual factors (e.g. classroom) explain effects at the student level. Conceptually, this study expanded knowledge of growth constructs by identifying an integrative (and parsimonious) underlying growth orientation factor – and showed that it had influence on academic outcomes. Whereas the multifactor approach to growth constructs (e.g. PB goals, growth mindset, mastery goals) typically seen in the literature offers specific information on the association between individual growth constructs and academic outcomes, Study 4 augmented this literature by demonstrating an underlying growth factor driving each specific growth construct that in turn impacted students' academic outcomes. This correlational design provided a valuable alternative view of students' growth constructs. Without question, many correlational studies will still need to focus on a specific growth factor (e.g. PB goals); however, in some future research projects, it may be more appropriate to consider the driving force behind these growth constructs (i.e. students' underlying growth orientation) such as that which can be modelled as a higher order factor in correlational (factor analytic) designs.

### *Limitations in correlational designs and future directions*

Although our focus has been on the opportunities that correlational designs can provide researchers and the unique insights they can yield for practice, there are limitations important to recognize and which are often addressed under other methodological and analytical approaches. First, it is often the case that correlational designs are based on self-report measures that are prone to bias. Thus, incorporating and corroborating with 'objective' data (e.g. actual/non-self-report achievement scores, others' observations or ratings) is important for the validity of interpretation. Our Studies 2 and 4, for example, included objective achievement data. Second, with self-report data there are potential issues with bias and unreliability. It is thus important to conduct statistical analysis that can account for unreliability and separate it from 'true variance.' For example, our studies did so through latent variable modelling that purges models of unreliability. Third, there is the reality of omitted variables whose inclusion may change the models being estimated and the conclusions drawn. This is where good foundations in theory are important to ensure the appropriate variables are accounted for. Fourth, the test of direction and causal ordering is (arguably) best determined under experimental designs. Any findings along directional lines in correlational designs should be followed by experimental work. These and other issues require attention when implementing a correlational research study.

### *The yields of substantive-methodological synergies*

Our integration of substantive and methodological concerns has been referred to as a substantive-methodological synergistic approach to research (Marsh and Hau 2007). In line with this approach, we sought to show that there is a mutually supportive role of both substantive and methodological dimensions to a research study – the effectiveness of one being heavily reliant on the effectiveness of the other. Thus, in concurrence with Marsh and Hau, we conclude that strong methodological research comprises creative solutions to substantive issues and strong substantive research is founded on robust and sometimes creative methodologies. We hope this review encourages substantive-methodological synergistic approaches to future correlational research programs that place students' academic growth as a foundation for optimal education and development through school – and beyond.

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