

Optimism Shapes Mindset: Understanding the Association of Optimism and Pessimism

William R. Dardick
George Washington University, Washington, USA

Elizabeth D. Tuckwiller
George Washington University, Washington, USA

ABSTRACT

The present study investigated our hypothesis of an underlying relationship between optimism/pessimism and implicit theories of intelligence. We investigated the psychometric properties of optimism and mindset scales in our sample, compared confirmatory factor analysis models of the scales, examined the full measurement model to confirm quality measurement of the final structural phase of investigation, and finally conducted two competing structural equation models. We found that the direct pathway from optimism to growth mindset was significant, and the pathway from pessimism to fixed mindset was also significant. However, there were no significant direct effects of optimism on fixed mindset or pessimism on growth mindset. Measurement, research, and practice implications are discussed.

Keywords: mindset, optimism/pessimism, Satorra and Bentler corrections, structural equation modeling

INTRODUCTION

The role of nonacademic factors in educational contexts relative to student performance and outcomes has gained considerable attention over the past two decades, and the relationships among these nonacademic variables and student outcomes is evident. The recent inclusion of nonacademic indicators in the *Every Student Succeeds Act* (2015), the most recent re-authorization of the 1965 Elementary and Secondary Education Act, signals a broad acceptance that factors other than those that are strictly academic are an important consideration in educational achievement. A number of nonacademic variables, such as implicit theories of intelligence (often referred to as “mindset”), grit, and optimism for example, and their relationships to student outcomes have been of recent interest. Although a good deal of research has been conducted on mindset (see Paunesku et al., 2015), its relationship to optimism has only been theoretically implied (Duckworth & Eskreis-Winkler, 2013) and preliminarily established through a few correlational studies (e.g., Tuckwiller, Dardick, & Kutscher, 2017).

There is a need to improve our understanding of how individuals’ levels of optimism (dispositional, expectancy and explanatory elements) relate to their mindset, and addressing that gap was a specific aim of the present study. We were curious to understand how one’s optimism and/or pessimism – that is one’s expectation of positive or negative future experiences – might shape one’s mindset toward expecting to improve intelligence (an optimistic expectation) or being unable to improve intelligence regardless of effort (a pessimistic expectation). We also hypothesized that optimism represents a broader expectation than mindset, and we speculated that this expectation of positive or negative future events might be a higher order factor in shaping one’s mindset expectations. Thus, to explore this hypothesis, we endeavored to model the relationship between optimism (and pessimism when we found evidence of the two-factor model) and fixed and growth mindset.

LITERATURE REVIEW

Implicit Theories of Intelligence

There has been a recent increase in research investigating implicit theories (e.g., De Castella & Byrne, 2015; Gal & Szamoskovi, 2016; Schroder, Dawood, Yalch, Donnellan, & Moser, 2015). Implicit theories can be conceptualized as beliefs individuals hold, about which they have no explicit awareness, which influence their choices, attitudes and behaviors. An

individual may hold implicit theories about a number of constructs including personality (Yeager, Trzesniewski, & Dweck, 2013), anxiety (Schroder et al., 2015), and intelligence (Blackwell, Trzesniewski, & Dweck, 2007). Implicit theories of intelligence are by far the most widely studied implicit theories and have been the focus of a large body of research regarding academic motivation and achievement. Much of the research in this domain is attributable to Dweck and colleagues (Dweck; 2000; Paunesku et al., 2015; Romero, Master, Paunesku, Dweck, & Gross, 2014; Yeager & Dweck, 2012) who have shown that students tend to hold one of two implicit theories about their intelligence: 1) an entity theory of intelligence (or “fixed mindset”) in which intelligence is thought to be fixed and not amenable to change or development, or 2) an incremental theory of intelligence (or “growth mindset”) in which the individual believes intelligence can grow and improve with effort and experience.

Empirical investigations of mindset provide clear evidence that these implicit theories are linked to academic achievement and motivation. For example, Romero et al. (2014) found that middle school students who believed that intelligence could be developed (that is, those who had a growth mindset) had higher grades and were more likely to enroll in advanced math courses. These results mirror other studies in which growth mindset has been associated with higher math grades (Blackwell et al., 2007) and advanced course enrollment (Paunesku et al., 2015). Implicit theories of intelligence have also been linked to academic motivation (Baird Scott, Dearing, & Hamill, 2009) and long-term academic achievement (Tetzner & Becker, 2017; Yeager et al., 2014). These data strongly suggest that how individuals think about intelligence and their beliefs about its malleability are related to overall academic motivation and outcomes. These understandings are especially important in light of the fact that mindset is responsive to intervention and changeable. Understanding the role of mindset in long-term academic outcomes and overall motivation and academic performance approaches facilitates potentially critical research related to academic outcomes and ultimately to life outcomes.

Researchers often measure mindset with the Implicit Theories of Intelligence Scale (ITI Scale) (Dweck, 2000). This eight-item scale measures respondents’ endorsements of either fixed mindset items (n=4) or growth mindset items (n=4) using a Likert-like scale. A number of studies have indicated that the scale is reliable and demonstrates good overall internal consistency, construct validity, and discriminant validity (De Castella & Byrne, 2015), and several studies have found the scale to be reliable and valid for students with learning disabilities (Baird et al., 2009; Tuckwiller et al., 2017).

General vs. self-theory. However, in a recent paper, De Castella and Byrne (2015) raised an important question regarding the ability of the ITI Scale to distinguish between an individual's beliefs about developing intelligence *in general* and an individual's beliefs about developing his or her own *personal intelligence*. They suggested that while the ITI Scale may reliably and validly measure an individual's beliefs about the ability to change intelligence *in general*, this general belief might not necessarily indicate that an individual believes that he or she can change his or her own *personal intelligence* (De Castella & Byrne, 2015). Indeed, some research suggests that judgments about others' abilities vs. one's own abilities are often quite disparate, based on a number of self-enhancing as well as self-diminishing biases (De Castella & Byrne, 2015). This led De Castella and Byrne (2015) to investigate whether there were subtle but important differences between students' general theories about the malleability of others' intelligence and their self-theories regarding the malleability of their own intelligence.

The Revised Implicit Theories of Intelligence (Self-Theory) Scale.

To conduct this investigation, De Castella and Byrne (2015) modified the original ITI Scale (Dweck, 2000) into a first-person self-theory scale by re-writing the original items into first person statements. For example, the original (and more general item) from Dweck's (2000) ITI Scale, "To be honest, you can't really change how intelligent you are" was revised to an explicit first-person statement on the Revised ITI Self-Theory Scale: "To be honest, I don't think I can really change how intelligent I am" (De Castella & Byrne, 2015; p. 261). All eight of the original ITI Scale items were revised into first person statements and the Revised ITI (De Castella & Byrne, 2015) was administered to 643 Australian high school students, evaluated psychometrically, and examined in terms of its predictive usefulness in relation to other constructs of interest (e.g., motivation and academic achievement).

The Revised ITI had good internal consistency overall ($\alpha = .90$) and good internal consistency for both the incremental mindset and entity mindset subfactors ($\alpha = .87$ and $\alpha = .92$, respectively). Using confirmatory factor analysis, they found that the two-factor model fit both the original ITI scale and the Revised ITI Scale. They also found high reliabilities for combined and reverse coded scales, suggesting that the measure also performed well as a unidimensional instrument (e.g., in the one factor model of the construct, the implicit theory of intelligence is indicated along a continuous dimension with incremental beliefs at one end of the scale and entity beliefs at the other.)

The data did indicate a more adequate model fit for the Revised ITI scale than the original ITI scale.

De Castella and Byrne's (2015) analyses and discussion indicated that the Revised ITI scale is useful. However, it is important to further evaluate the indicators, considering model fit was better for the two-factor model, but RMSEA criteria of .08 was only met for the two-factor model on the Revised ITI scale, and not met for the original ITI scale. What this calls into question is not if the competing two factor model is superior; it clearly is the more appropriate model based on all incremental model fit indices. We instead question the absolute measure of good fit since RMSEA was in a range that was neither good nor bad, and we cannot say there is "relatively good fit between the hypothesized model and the observed data" (Hu & Bentler, 1999). Therefore, although there was evidence that the scale was useful, the model fit warranted additional evaluation, which we discuss later in more detail.

To investigate the usefulness of examining a self-oriented implicit theory compared to a general implicit theory, the researchers conducted t-tests to compare scores on both measures. These analyses indicated a small but statistically significant difference on the original ITI Scale vs. the Revised ITI scale, indicating that students more strongly endorsed a fixed mindset view of intelligence when considering the malleability of others' intelligence as compared to the malleability of their own intelligence ($d=.17$). In other words, students believed that their own intelligence was more malleable than the intelligence of others. Furthermore, two-step hierarchical regression analyses indicated that while both scales accounted for a significant amount of variance in: achievement goals, performance approach, performance avoidance, mastery approach, helplessness attributions, self-handicapping, truancy, disengagement, and grades, scores on the Revised ITI Self-Theory Scale predicted, above and beyond the General ITI Scale, unique outcome variance on these dependent variables. The researchers interpreted these results to mean that "the self-theory scale was consistently superior when both measures were used to predict the dependent variables" (De Castella & Byrne, 2015; p. 257).

Optimism

The construct of optimism has been explored by researchers interested in both its measurement as well as its outcome correlates. Particularly for education settings, a few researchers have explored how optimism is related to important school-based outcomes. For example, Boman, Smith and Curtis (2003) found that more optimistic children had less hostility toward school and were less likely to engage in angry displays in

school settings. They also found that optimism was linked to more classroom involvement, an important factor in overall school engagement. However, in general, optimism has received notably less research attention in the field of education than has mindset.

The optimism construct has a number of differing conceptualizations, but two notions of particular interest relative to student outcomes are 1) optimism as a disposition – that is, a relatively stable personality trait (e.g., Scheier & Carver, 1985), and 2) optimism as a cognitive process (Buchanan & Seligman, 1995). In research exploring dispositional elements of optimism as well as expectancy (a cognitive component of optimism), both have been related to nonacademic student outcomes such as school involvement, and dispositional optimism has been noted as specifically important to counteract negative expectations (Boman & Yates, 2001).

More recently, optimism, especially as an explanatory style, has been conceptually and theoretically related to mindset (see Duckworth & Eskreis-Winkler, 2013), but there is very limited empirical data relative to the associations between optimism and implicit theories of intelligence. There *is*, for example, evidence of a relationship between optimism and perceived controllability of events (a related but distinct concept from the malleability component of implicit theories; see Harris, 1996), and a recent study found a clear correlation between optimism and implicit theories of intelligence in adolescents with learning disabilities (Tuckwiller et al., 2017). However, there is clearly a need to improve our understanding of how individuals' levels of optimism (dispositional, expectancy and explanatory elements) relate to their implicitly held theories of intelligence. Addressing that gap was a specific aim of the present study.

To measure optimism, many consider the Life Orientation Test-Revised (LOT-R) (Scheier, Carver, & Bridges, 1994) to be the gold standard in measurement. The LOT-R is a 10-item instrument designed to measure dispositional, or trait level, optimism. Three items measure optimism, three items measure pessimism, and four items (filler; not scored) are designed to detect faking positive. The scale has been found to have acceptable reliability and validity with numerous populations (Gustems-Carnicer, Calderón, & Santacana, 2017; Hirsch, Britton, & Conner, 2009; Scheier et al., 1994). While some studies suggest that a unidimensional construct (with optimism distributed along a continuum from low to high) demonstrates sufficient fit (e.g. Vautier, Raufaste, & Cariou, 2003; Scheier et al., 1992), other studies indicate that a two-factor solution with optimism and pessimism functioning as separate factors is more appropriate (e.g., Gustems-Carnicer et al., 2017; Ottati & Noronha, 2017; Tuckwiller et al., 2017). Thus, in the present study, we explored the data to interpret the best fitting model for the data.

Guiding Conceptual Framework

Beliefs and expectations can significantly shape life experiences and outcomes. Some expectations represent acceptance of a “truth” without evidence or prior experience (akin to a “belief”), while other expectations may be shaped and contoured by past experiences. There is evidence that although many of the expectations an individual holds are conscious, not all of them are, and furthermore that expectations, conscious or not, alter an individual’s experience of the self and the world (Berdik, 2013). An individual’s mindset may well function initially as a *belief*, as Dweck and others note, that is not held consciously. Early in life, one may hold a belief that with effort and experience, one can increase intelligence (growth mindset) or one may believe that intelligence is immutable and static (fixed mindset). However, over time, and with repeated experiences of success and failure, one may come to hold, based on those past experiences, a strong expectation (conscious or not) about one’s ability to shape intelligence. Similarly, optimism has been viewed as a disposition (similar to a belief in that it can exist in the absence of evidence) as well as an expectation that is shaped by past experiences. Compelling evidence of the power of expectation on outcomes suggests that the same behaviors can result in drastically different outcomes, based upon expectations, *whether we are aware of those expectations consciously or not* (Birdek, 2013).

As we considered the potential involvement of optimism in implicit theories writ large, we realized that it is impossible to conceptualize the notion of a theory of intelligence (conscious or not) without the construct of expectation. Simply put, does an individual expect that their effort and persistence will result in a change to their intelligence? It is similarly impossible to think about optimism, especially relative to school-age individuals, without the notion of expectation; does one expect good things to happen or negative things to happen in terms of academic outcomes and experiences? Thus, we were curious to understand how one’s disposition toward optimism and/or pessimism – that is one’s *expectation* of positive or negative future experiences – might shape his or her mindset toward expecting to improve intelligence (an optimistic expectation) or being unable to improve intelligence regardless of effort (a pessimistic expectation). In short, expectations shape outcomes, and optimism and mindset are both comprised, at least in part, by expectation. We also hypothesized that optimism is a broader expectation than mindset, and we speculated that this expectation of positive or negative future events might be a higher order factor in shaping one’s mindset expectations. Thus, to explore this hypothesis, we endeavored to model the relationship between optimism (and pessimism

when we found evidence of the two-factor model) and fixed and growth mindset.

The Present Study

The purpose of the current pilot study was three-fold, with an overarching goal to help explain the relationship of optimism and pessimism with growth and fixed mindset. First, we were interested in the use of the Revised Implicit Theory of Intelligence Self-Theory Scale (De Castella & Byrne, 2015) for American university students. Although the original ITI Scale (Dweck, 2000) has been used in research with university students, the Revised ITI had not been, and we were eager to evaluate its psychometric properties with a university population.

Second, in the measurement stage of investigation, we aimed to follow up on research by De Castella and Byrne (2015) regarding the comparison of one and two factor confirmatory factor analysis (CFA) models for both the original ITI and the Revised ITI. In doing so, we split the measurement phase into a preliminary phase and a full measurement model phase. In the preliminary measurement phase, four CFA models were examined when the two mindset scales (general and self-theory) were combined to explore evidence of the number of factors in the two scales. We wanted to know if a higher order mindset factor exists, or alternatively provide evidence for clear self-theory vs. general theory and fixed vs. growth mindset factors as a four-factor model. We finished the preliminary stage by investigating the one- and two-factor models for optimism and pessimism. The full measurement CFA model phase examined all mindset factors with both optimism and pessimism to examine misspecification and add confidence to the measurement portion of our study.

Finally, we wanted to pilot competing structural equation models (SEM) to model and explain the multiple factors in the mindset and optimism scales for our population. The model we considered was driven by theory and research. Given past research, our expectation was to find evidence of two-factor models for all three scales (optimism, general mindset, and self-theory mindset) for a total of six factors. We also expected that optimism and pessimism would have a large effect on growth and fixed factors, respectively (see conceptual diagrams in the next section for further detail).

In both the second and third stage of the analysis, we also addressed the essential issue to consider techniques that can account for non-normality that often arises for Likert scale data when considering data-model fit (Jöreskog, 1993; Lee & Bentler, 1990; Muthén, 1993; Muthén & Kaplan, 1985, 1992; Savalei, 2014; Simsek & Noyan, 2012). Likert type scales are widely used as if the data are continuous without correction for statistical

model-fit indices. In the present study, we corrected CFA and SEM fit-indices using techniques developed by Satorra and Bentler (1994), discussed further in the Methods section.

The Conceptual Path Diagram

Figure 1 represents our conceptual model, which displays the latent variables related to optimism and mindset and how we theorized they were related to each other. Only the structural model is presented, as items in the measurement portion of the model were indicators only for the appropriate subscales and no cross-loading was permitted (e.g., general growth mindset items were only indicators of the factor of the same name). The first, model 1 (Fig. 1), shows an uncrossed path diagram, in which the parent relationship of optimism has a direct path to growth mindset factors as children, and the parent relationship of pessimism has a direct path to fixed mindset factors as children. However, in model 1 we did not cross over to predict fixed mindset from optimism and growth mindset from pessimism.

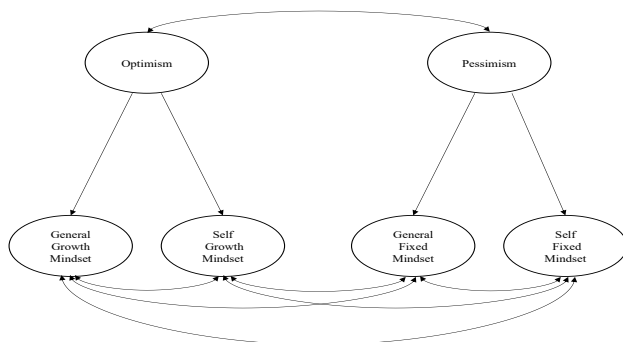


Figure 1. Conceptual structural model for optimism and mindset uncrossed. Paths are permitted: from optimism to growth factors but not fixed factors; from pessimism to fixed factors but not growth factors. Optimism and pessimism are correlated. Mindset factors are correlated.

We compared this hypothesized measurement model 1 to model 2 (Fig. 2) in which paths were fully crossed, permitting paths from optimism and pessimism as parents to all four factors (that is, general fixed mindset, general growth mindset, self-theory fixed mindset, and self-theory growth mindset). This model resulted in eight total paths of interest. Our pilot research questions were based on conceptual models. We wanted to examine

whether the crossover paths to predict fixed mindset from optimism and growth mindset from pessimism would be significant and if adding these paths would significantly increase the overall model fit. We hypothesized that the crossover paths would not be significant, nor add significantly to the overall model.

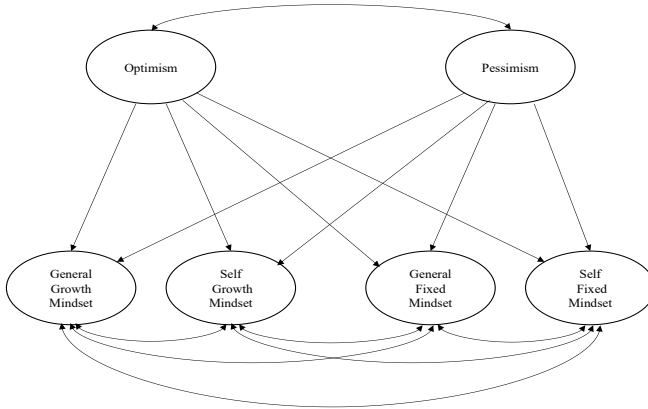


Figure 2. Conceptual structural model for optimism and mindset fully crossed. Optimism and pessimism have paths to all four mindset factors. Optimism and pessimism are correlated. Mindset factors are correlated.

In the development of these models (Figs.1 and 2) from theory, it is important to note that model 2 is an equivalent model to the full measurement model in phase one, with the distinction of having eight direct paths instead of correlations among those variables. All equivalent models have equal overall model fit, but it is the structural comparison between the measurement model and structural model 2 that is interesting to us. Using model 2 as a competing model to model 1 helped us understand whether the model with crossed loadings had better structural fit than model 1 with only uncrossed paths. We also left our modeling open to the possibility that empirically an additional model might arise (e.g., two factors for mindset instead of four) when investigating in the measurement phase.

RESEARCH METHOD

Participants

Participants were selected through a stratified (gender, ethnicity, and degree program) random sample of 2,000 students from a mid-Atlantic university to represent the university population and invited to participate via email. Students were from undergraduate, graduate and non-degree programs across the university. Two hundred and ninety students submitted the survey; however, 45 participants submitted no responses or such limited information that the responses and demographics were missing substantial data and could not be used in the analysis. Thus, 245 undergraduate and graduate students responded completely to the scales.

Demographic information for the initial 2,000 participants selected was acquired from the university, but the 245 participant respondents self-reported demographics on the survey, so students could choose to remain anonymous. Tables 1 through 3 provide a detailed breakdown of demographic information on gender, ethnicity and degree for both the initial sample and responding participants. The response rate for student participants who completed the survey was 12.25% (14.50% including those who started but did not complete the survey). Response rate was impacted by students not using university email or not using university emails as a primary source. The responding sample identified as more female (69.80%) and Caucasian (63.67%) when compared to the initially selected participants who were 58.50% female and 51.90% Caucasian. A further investigation of the discrepancy in ethnicity revealed that those identified as Asian (9.55%) in the initial sample were overrepresented among those who responded to the survey (16.73%), while the "Other" ethnicity category (15.85% in the initial sample) was underrepresented in responding participants (2.45%). Average age of the initial selected participants was $M = 27.65$ ($SD = 8.95$) which was similar to the responding groups' age of $M = 26.3$ ($SD = 8.99$) years. Approximately 57.95% of the initially sampled participants were in graduate and doctoral programs comparable to 60% of respondents.

Table 1
Ethnicity of Research Participants

	Participants Sampled		Respondents	
	<i>f</i>	%	<i>f</i>	%
American Indian or Pacific Islander	9	0.45	1	0.41
Asian	191	9.55	41	16.73
Black	200	10.00	18	7.35
Hispanic	127	6.35	16	6.53
Other	317	15.85	6	2.45
Unknown	118	5.90	7	2.86
White	1038	51.90	156	63.67
Total	2000	100	245	100

Ethnicity for participants sampled was acquired by the school while ethnicity of respondents was self-selected.

Table 2
Gender of Research Participants

	Participants Sampled		Respondents	
	<i>f</i>	%	<i>f</i>	%
Female	1170	58.5	171	69.8
Male	825	41.25	69	28.2
Prefer not to say	5	0.25	1	.4
Missing	0	0	4	1.6
Total	2000	100	245	100

Table 3
Degree program

	Participants Sampled		Respondents	
	<i>f</i>	%	<i>f</i>	%
Bachelor's degree	812	40.60	92	37.6
Graduate degree	1159	57.95	147	60.0
Non-degree	29	1.45	6	2.4
Total	2000	100	245	100

Procedure

The university administration assisted in selection through a stratified random sample of 2,000 students who were invited to participate in the study via email. Students were asked to complete a survey delivered via the Qualtrics© platform with an option to enter a raffle for a new iPad© mini to incentivize participation. Participants were provided information regarding the survey and informed consent was obtained. Participants completed a survey, which included the items from the Implicit Theories of Intelligence Scale (ITI-General) (Dweck, 2000), the Revised Implicit Self-Theory Scale (ITI-Self) (De Castella & Byrne, 2015), and the Life Orientation Test - Revised (LOT-R) (Scheier et al., 1994). Directions indicated that responses would remain anonymous and that there were no right or wrong answers.

Measures

General and self-theory mindset scales. Dweck's Implicit Theories of Intelligence Scale (ITI-General) (Dweck, 2000) is comprised of four items that measure the fixed mindset factor and four that measure the growth mindset factor. The scale is designed to measure an individual's beliefs about the ability to change intelligence with effort and experiences. De Castella and Byrne (2015) developed the Revised Implicit Theories of Intelligence (Self-Theory) Scale (ITI-Self) from the original ITI-General Scale (Dweck, 2000), with all items reworded into first-person statements. The scale is designed to measure very specifically an individual's beliefs in his or her own ability to change his or her own personal intelligence. Both scales have demonstrated good internal consistency in past research ($\alpha = .87$ for ITI-General and $\alpha = .90$ for ITI-Self-Theory).

Optimism. The Life Orientation Test – Revised (LOT-R) (Scheier et al., 1994) is a 10-item instrument designed to measure dispositional optimism. There are three items to measure optimism, three to measure pessimism, and four filler items to detect faking positive. A psychometric evaluation of the instrument ($n = 2,055$), yielded an $\alpha = .78$ (Scheier et al., 1994). There is an ongoing discussion in the literature regarding the unidimensionality (or lack thereof) of optimism as measured on the LOT-R. While some investigations suggest that the LOT-R supports the notion of optimism as a unidimensional construct (on which optimism is experienced along a spectrum from low to high), a substantial number of studies have found evidence for a two-factor solution for LOT-R scores, indicating that optimism and pessimism are distinct and dissociable constructs, both of which may be expressed at high or

low levels (e.g., Gustems-Carnicer et al., 2017; Ottati & Noronha, 2017; Tuckwiller et al., 2017).

Scale scores. Participants selected their amount of endorsement for items using a 6-point Likert response scale ranging from strongly disagree to strongly agree without a neutral response. All three scales (ITI-General, ITI-Self, and LOT-R) used this 6-point Likert response scale. Each aggregate score was created by summing the scores of all items on each scale. The ITI General and ITI Self each have a score range from 0 to 40. The LOT-R scores, when assessed as a unidimensional construct, have a score range from 0 to 30, but when broken out into a two-factor model, the LOT-R optimism (LOT-RO) subscale ranges 0 to 15 and pessimism subscale (LOT-RP) ranges from 0 to 15.

Table 4

Item Analysis for Scales

ITIG	M	SD	r*	ITIS	M	SD	r*	LOTR	M	SD	r*
ITIG	3.95	1.20	0.78	ITIS	4.22	1.18	0.79	LOTR	3.66	1.24	0.57
1R				1R				1			
ITIG	4.09	1.21	0.84	ITIS	4.23	1.16	0.90	LOTR	3.86	1.08	0.69
2R				2R				3R			
ITIG	3.99	1.13	0.75	ITIS	4.40	1.11	0.84	LOTR	4.16	1.18	0.66
3				3				4			
ITIG	4.12	1.13	0.85	ITIS	3.93	1.24	0.84	LOTR	3.89	1.18	0.76
4R				4R				7R			
ITIG	3.82	1.09	0.80	ITIS	4.19	1.18	0.90	LOTR	4.00	1.17	0.71
5				5R				9R			
ITIG	3.67	1.29	0.80	ITIS	4.17	1.13	0.82	LOTR	4.36	1.13	0.76
6R				6				10			
ITIG	3.96	1.11	0.74	ITIS	4.22	1.08	0.86				
7				7							
ITIG	3.85	1.16	0.80	ITIS	4.32	1.11	0.82				
8				8							

Note: ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R). Items are used for each scale are listed under the scale. R = reverse coded item. Total N=245, r* = Item-Total Correlation.

Psychometric properties. We evaluated the quality of the measures with classical measures. Internal consistency for all three scales was satisfactory with ITI General Scale $\alpha = .943$; ITI Self Scale $\alpha = .960$; and the LOT-R $\alpha = .882$. The mean (M) and standard deviation (SD) of these items can be found in Table 4. Item-total correlations r^* were all strong positive values significant on all scales at $p < .001$, indicating that participants who

endorsed agreement with an item had general agreement value for the overall scale. Correlations among all scales/subscales (ITI General, ITI Self, and LOT-R) were statistically significant. See Tables 5 and 6 for correlations. All of the relationships were positive. Prior to analysis, all items endorsing fixed mindset and pessimism were reverse coded so that higher scores on each of the scales indicated higher self-reported levels on the applicable scale.

Table 5
Correlations Among Scales

	ITIG	ITIS	LOTR
ITIG	1	0.881	0.279
ITIS		1	0.336
LOTR			1

Note: significant at the <.01 level. ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R).

Table 6
Correlations Among Sub-scales

	ITIG_G	ITIS_G	LOTR_OPT	ITIG_F	ITIS_F	LOTR_PES
ITIG_G	1.00	0.84	0.26	0.79	0.73	0.25
ITIS_G		1.00	0.31	0.79	0.86	0.27
LOTR_OPT			1.00	0.17	0.26	0.66
ITIG_F				1.00	0.85	0.27
ITIS_F					1.00	0.32
LOTR_PES						1.00

Note: significant at the <.01 level. ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R). G = growth mindset, F = fixed mindset, OPT = optimism, PES = pessimism.

Analysis

All analysis was conducted using the SAS (2016) platform. Likert data is often non-normal which leads to issues when attempting to use model fit statistics to determine the quality of a model. To account for this issue prevalent in scaled measures, we utilized a form of Maximum Likelihood Estimation (MLE) in SAS proposed by Satorra and Bentler (1994) that uses a sandwich-like formula to adjust chi-square and associated standard errors and model fit indices (SAS, 2016). This estimation method, MLSB in PROC CALIS, is appropriate for either normal or non-normal data and computes

model fit statistics based on scaled chi-squares more appropriate for this type of data. Practitioners typically justify data as continuous, normal data; however, this is often not the case and it can impact fit measures (e.g., comparative fit index (CFI); root mean square error of approximation (RMSEA) in latent models) (Simsek & Noyan, 2012). The METHOD=MLSB is appropriate for MLE when data are normal or non-normal (SAS, 2016).

To evaluate the best fitting models, we considered several fit indices in addition to reporting χ^2 . The Akaike Information Criterion (AIC; Akaike, 1974) is used as a relative measure modifying model fit through complexity of the model, where smaller values indicate better incremental fit. Standardized root mean square residual (SRMR) and root mean square error of approximation (RMSEA) are absolute fit measures, where values smaller than 0.08 are desirable and below 0.05 indicate good fit. For comparative fit index (CFI), the recommended cutoff value is .95 to be considered good fit with values under .90 considered poor fit (Hu & Bentler, 1995, 1998, 1999; Kline, 2011; MacCallum, Browne, & Sugawara, 1996). Further, as discussed in the Methods section, we used the Satorra-Bentler adjustment in SAS (2016) for fit indices under maximum likelihood with scaled model fit chi-square statistics and sandwich-type standard error estimation (MLSB) to account for the polytomous Likert scale data used in the analysis. Specifically, MLSB adjusted chi-square, model fit indices, and standard errors used in this study but not standardized root mean square residuals (SRMR).

In the measurement phase of our analysis, we used confirmatory factor analysis (CFA) models to assess scales and subscales of our measures. This stage of investigation served as a measurement phase to diagnose satisfactory fit of the factors used and, if necessary, to correct any misfit issues prior to our final stage of investigation. In the preliminary measurement phase, we first explored the one, two, four and higher order factor models to best explain the two mindset scales: ITI-General and ITI-Self. Next, we explored the one- and two-factor model for LOT-R. Finally, in our full measurement phase, we used six factors from the ITI-General, ITI-Self and LOT-R in a CFA model to ensure the quality of the measurement model prior to examining the structural portion of the model. Structural equation model (SEM) using the functions for MLSB in SAS (2016) was used during the final structural stage of analysis to compare best fitting models based on our findings in stage two. In our two conceptual models described earlier we used optimism factor(s) as exogenous unobserved parents related to endogenous mindset factors and compared model fit (see Figures 1 and 2).

RESULTS

In the measurement phase, we first investigated the two mindset scales (general and self-theory) together and compared them as a one, two, four and a higher-order factor model. We also explored the two-factor LOT-R model with three optimistic items on a separate factor from the three pessimistic items. A summary covariance matrix used for this analysis is available in Table 7. As presented earlier in the introduction, our explanation of the two factors arising out of each mindset scale (that is, the growth mindset and the fixed mindset) is that optimism drives responses on growth mindset items and pessimism influences fixed mindset items. We explored two competing models in the structural phase.

Preliminary Measurement Phase

Combined ITI-General and ITI-Self Mindset Scales. We used the combined ITI-General and ITI-Self scales to explore a potential higher order overarching mindset factor, as well as to explore evidence for clear self-theory vs. general theory factors (e.g., we compared the one factor (overarching mindset factor), two factor (only general and self-mindset factors), four factor (general growth mindset, general fixed mindset, self-growth mindset, self-fixed mindset factors), and a five-factor model (a general higher-order mindset factor and four first order factors). The four-factor model fit the data better than the other three models, $\chi^2(98) = 161.84$, AIC=237.85. For ITI-General Scale and the ITI-Self-Theory Scale, the four factors had four items measuring growth mindset and four measuring fixed mindset loaded on separate factors from each of the two scales. Examination of these indices showed acceptable model fit CFI = .99, RMSEA = .05, and SRMR = .03. Although the higher order factor model did not fit as well as the four-factor model, it did fit the data adequately according to the model fit indices in Table 8.

LOT-R. The two-factor model outperformed the one-factor model with $\chi^2(8) = 13.75$. AIC =39.75 (see Table 7). Examination of these indices showed reasonable model fit CFI = .99, RMSEA = .05, and SRMR = .03.

Full Measurement Model

The full CFA model in Figure 3 contains six factors: General Growth Mindset (GGM) and General Fixed Mindset (GFM) from the ITI- General scale; Self Growth Mindset (SGM) and Self Fixed Mindset (SFM) from the ITI-Self, scale; Optimism and Pessimism from the LOT-R scale. Model fit indices detailed in Table 7 showed sufficient evidence for use of this measurement model in the structural phase of the study, $\chi^2(194) = 297.14$,

AIC =415.14 (see Table 7). Further examination of indices also showed reasonable model fit CFI = .98, RMSEA = .047, and SRMR = .037. Standardized and unstandardized loading are presented in Table 9.

Table 8

Fit Indices for Confirmatory Factor Models and Structural Equation Models

Model	SB-Scaled χ^2	df	AIC	GFI	CFI	RMSEA	SRMR
Confirmatory models for mindset (ITI-General & ITI-Self)							
One-Factor	370.744	104	434.744	.671	0.9351	.103 .091, .114	.054
Two-Factor	292.673	103	358.673	.697	0.954	.087 .077, .099	.049
Four-Factor	161.845	98	237.845	.826	0.985	.052 .037, .066	.032
Higher order five Factor	190.888	100	262.887	.811	0.978	.061 .045, .074	.041
Confirmatory models for LOT-R							
One-Factor	38.407	9	62.407	0.931	0.942	0.116 0.08, 0.157	0.047
Two-Factor	13.747	8	39.747	.977	0.989	0.054 0, 0.102	0.027
Full measurement model and structural models							
Measurement Model	297.141	194	415.141	.834	.979	.047 (0.36, 0.057)	.037
Structural Model 1	300.803	198	410.803	.833	.979	.046 (0.035, 0.056)	.039
Structural Model 2	297.141	194	415.141	.834	.979	.047 (0.036, 0.057)	.037

Note: The preliminary four confirmatory factor models for mindset (subheading 1), the two confirmatory factor models for LOTR (subheading 2), the full confirmatory factor model for the measurement phase and the two conceptual structural models from the structural phase (subheading 3) of the investigation are all presented here. SB-Scaled χ^2 = Satorra-Bentler adjusted chi-square, df = degrees of freedom, AIC = Akaike Information Criteria, GFI = Goodness of fit index, CFI = comparative fit index, RMSEA = root mean square error of approximation with 90% confidence intervals, SRMR = standardized root mean square residual.

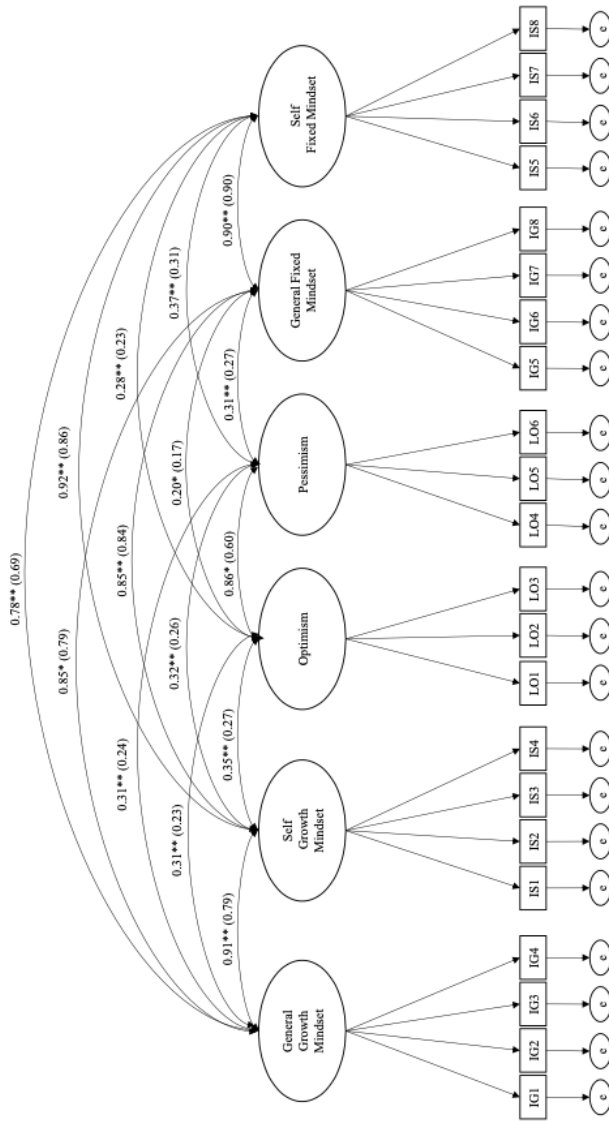


Figure 3. Measurement model - Fully Correlated Confirmatory Factor Analysis for all factors. ** designates significant standardized pathway at $p < .001$, * indicates pathway significant at $p < .01$ with unstandardized estimate in parentheses. All indicator pathways for scaled items are significant at $p < .001$ with standardized paths ranging from .66 to .94 with mean = .85. All standardized and unstandardized loadings are presented in Table 9. IG = Implicit Theories of Intelligence Scale (ITI-General), IS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LO = Life Orientation Test-Revised (LOT-R). e=error.

Table 9

Full Measurement Model: Unstandardized and Standardized Effects

Path(s)		Unstandardized	Standardized	S.E.	P	
GFM	==>	ITIG1R	1	0.855	0.042	<.001
GFM	==>	ITIG2R	1.079	0.916	0.015	<.001
GFM	==>	ITIG4R	0.998	0.904	0.019	<.001
GFM	==>	ITIG6R	1.053	0.836	0.026	<.001
GGM	==>	ITIG3	1	0.796	0.039	<.001
GGM	==>	ITIG5	1.046	0.869	0.023	<.001
GGM	==>	ITIG7	1.015	0.823	0.038	<.001
GGM	==>	ITIG8	1.106	0.858	0.022	<.001
OPT	==>	LOTR1	1	0.658	0.049	<.001
OPT	==>	LOTR4	1.077	0.744	0.039	<.001
OPT	==>	LOTR10	1.161	0.841	0.036	<.001
PES	==>	LOTR3R	1	0.793	0.033	<.001
PES	==>	LOTR7R	1.22	0.886	0.025	<.001
PES	==>	LOTR9R	1.067	0.779	0.044	<.001
SFM	==>	ITIS1R	1	0.825	0.055	<.001
SFM	==>	ITIS2R	1.107	0.933	0.018	<.001
SFM	==>	ITIS4R	1.133	0.89	0.016	<.001
SFM	==>	ITIS5R	1.137	0.939	0.017	<.001
SGM	==>	ITIS3	1	0.866	0.029	<.001
SGM	==>	ITIS6	1.028	0.872	0.027	<.001
SGM	==>	ITIS7	1.015	0.898	0.029	<.001
SGM	==>	ITIS8	1.016	0.875	0.023	<.001
GFM	<=>	GGM	0.789	0.853	0.029	<.001
GFM	<=>	SFM	0.901	0.900	0.018	<.001
GGM	<=>	SFM	0.687	0.780	0.034	<.001
GFM	<=>	SGM	0.836	0.852	0.023	<.001
GGM	<=>	SGM	0.786	0.909	0.018	<.001
SFM	<=>	SGM	0.860	0.920	0.026	<.001
OPT	<=>	GFM	0.170	0.203	0.070	.004
OPT	<=>	GGM	0.225	0.306	0.073	<.001
OPT	<=>	SFM	0.226	0.284	0.067	<.001
OPT	<=>	SGM	0.271	0.347	0.070	<.001
PES	<=>	GFM	0.271	0.309	0.067	<.001

PES	⟷	GGM	0.235	0.305	0.069	<.001
PES	⟷	SFM	0.310	0.371	0.060	<.001
PES	⟷	SGM	0.258	0.315	0.064	<.001
PES	⟷	OPT	0.598	0.855	0.036	<.001

Note: Factors are labeled: GGM= General Growth Mindset, SGM= Self Growth Mindset, GFM= General Fixed Mindset, SFM= Self Fixed Mindset, OPT= Optimism, PES=Pessimism. Items are labeled: ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R). R=reverse coded item. R=reverse coded. S.E. is the standard error. P is significance level.

Structural Phase

Model 1 allowed direct paths from optimistic paths to growth mindset factors and pessimistic paths to fixed mindset factors (both general and self), permitting four paths total. This model represented our theoretically derived uncrossed model. Model 2 permitted paths from optimism and pessimism to all four factors, eight paths total, and is a more general, fully crossed model for nesting purposes. This crossed model included all of the pathways from model 1 plus pathways from optimism to fixed mindset factors and pessimism to growth mindset factors. In both models, the six factors (optimism, pessimism, general growth mindset, self-theory growth mindset, general fixed mindset, and self-theory fixed mindset) were scaled by fixing the variance to 1. Overall, models 1 and 2 had very similar fit. We selected the simple model 1 as having better data-model fit for several reasons. The chi-square difference test for nested models is $297.141 - 300.803 = 3.662$ (4) which is not significant, meaning there is no significant improvement to fit the more complex model. As can be seen in Table 7 for model 1, AIC = 410.80 has better comparative fit than model 2 AIC=415.14. Models were not re-specified. Data-model fit is presented in Table 7 using the same indices as used in measurement stage: SB-Scaled χ^2 , AIC, GFI, CFI, RMSEA, and SRMR. All data-model fit indices were similar, leading us to be more inclined to consider parsimony for the models.

The standardized and unstandardized parameter estimates for model 1 and model 2 can be found in Tables 10 and 11, respectively. The final theoretically driven structural model 1 and competing structural model 2 can be found in the path diagrams in Figures 4 and 5 to help explain the effects of the model. When examining standardized parameter estimates for measured indicators on the latent factors in both models, all indicators were significant at $p < .001$. Further, all pathways were significant for model 1, the uncrossed model. In model 2, there were nonsignificant pathways for six out of the eight effects. The direct effects in model 2 that were nonsignificant between factors

were helpful in determining which model to choose beyond examination of fit indices. All crossed relationships were nonsignificant, meaning that when optimism was used to predict fixed mindset factors and pessimism was used to predict growth mindset factors, all four of these pathways were nonsignificant. Additionally, the pathways in model 2 from optimism to both growth mindset factors were nonsignificant. Although nonsignificant, the pathways from optimism to fixed mindset factors were negative.

Table 10

Structural Model 1: Unstandardized and Standardized Effects

Path(s)	Unstandardized	Standardized	S.E.	P
GFM ==> ITIG1R	1	0.854	0.042	<.001
GFM ==> ITIG2R	1.080	0.916	0.015	<.001
GFM ==> ITIG4R	1.000	0.906	0.019	<.001
GFM ==> ITIG6R	1.054	0.837	0.025	<.001
GGM ==> ITIG3	1	0.798	0.039	<.001
GGM ==> ITIG5	1.046	0.871	0.023	<.001
GGM ==> ITIG7	1.017	0.826	0.037	<.001
GGM ==> ITIG8	1.107	0.860	0.022	<.001
OPT ==> LOTR1	1	0.657	0.049	<.001
OPT ==> LOTR4	1.084	0.748	0.039	<.001
OPT ==> LOTR10	1.162	0.841	0.037	<.001
PES ==> LOTR3R	1	0.795	0.033	<.001
PES ==> LOTR7R	1.218	0.887	0.026	<.001
PES ==> LOTR9R	1.064	0.779	0.043	<.001
SFM ==> ITIS1R	1	0.826	0.054	<.001
SFM ==> ITIS2R	1.107	0.934	0.018	<.001
SFM ==> ITIS4R	1.133	0.890	0.016	<.001
SFM ==> ITIS5R	1.137	0.939	0.017	<.001
SGM ==> ITIS3	1	0.868	0.028	<.001
SGM ==> ITIS6	1.027	0.874	0.026	<.001
SGM ==> ITIS7	1.015	0.900	0.029	<.001
SGM ==> ITIS8	1.016	0.877	0.023	<.001
GFM <=> GGM	0.715	0.765	0.046	<.001
GFM <=> SFM	0.791	0.786	0.040	<.001
GGM <=> SFM	0.597	0.668	0.044	<.001
GFM <=> SGM	0.755	0.761	0.043	<.001

GGM	⟷	SGM	0.685	0.778	0.044	<.001
SFM	⟷	SGM	0.760	0.800	0.045	<.001
OPT	⟷	PES	0.594	0.848	0.034	<.001
OPT	⟹	GGM	0.389	0.349	0.064	<.001
OPT	⟹	SGM	0.450	0.379	0.059	<.001
PES	⟹	GFM	0.366	0.306	0.063	<.001
PES	⟹	SFM	0.431	0.376	0.053	<.001

Note: Factors are labeled: GGM= General Growth Mindset, SGM= Self Growth Mindset, GFM= General Fixed Mindset, SFM= Self Fixed Mindset, OPT= Optimism, PES=Pessimism. Items are labeled: ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R). R=reverse coded item. R=reverse coded. S.E. is the standard error. P is significance level.

Table 11

Structural Model 2: Unstandardized and Standardized Effects

Path(s)		Unstandardized	Standardized	S.E.	P	
GFM	⟹	ITIG1R	1.000	0.861	0.031	<.001
GFM	⟹	ITIG2R	1.109	0.925	0.013	<.001
GFM	⟹	ITIG4R	1.027	0.915	0.016	<.001
GFM	⟹	ITIG6R	1.084	0.852	0.022	<.001
GGM	⟹	ITIG3	1.000	0.839	0.025	<.001
GGM	⟹	ITIG5	0.977	0.887	0.019	<.001
GGM	⟹	ITIG7	0.948	0.844	0.033	<.001
GGM	⟹	ITIG8	1.032	0.875	0.018	<.001
OPT	⟹	LOTR1	1.000	0.733	0.021	<.001
OPT	⟹	LOTR4	0.964	0.773	0.031	<.001
OPT	⟹	LOTR10	1.037	0.86	0.029	<.001
PES	⟹	LOTR3 R	1.000	0.839	0.017	<.001
PES	⟹	LOTR7 R	1.144	0.902	0.02	<.001
PES	⟹	LOTR9 R	0.999	0.805	0.036	<.001
SFM	⟹	ITIS1R	1.000	0.85	0.038	<.001
SFM	⟹	ITIS2R	1.077	0.942	0.015	<.001
SFM	⟹	ITIS4R	1.102	0.902	0.013	<.001
SFM	⟹	ITIS5R	1.105	0.946	0.015	<.001
SGM	⟹	ITIS3	1.000	0.888	0.021	<.001

SGM	==>	ITIS6	1.008	0.889	0.023	<.001
SGM	==>	ITIS7	0.995	0.912	0.025	<.001
SGM	==>	ITIS8	0.996	0.892	0.019	<.001
GFM	<==>	GGM	0.878	0.787	0.034	<.001
GFM	<==>	SFM	0.904	0.789	0.037	<.001
GGM	<==>	SFM	0.795	0.700	0.031	<.001
GFM	<==>	SGM	0.891	0.789	0.033	<.001
GGM	<==>	SGM	0.914	0.816	0.032	<.001
SFM	<==>	SGM	0.943	0.821	0.037	<.001
OPT	<==>	PES	0.875	0.875	0.02837	<.001
OPT	==>	GGM	0.150	0.142	0.175	0.415
OPT	==>	SGM	0.282	0.265	0.161	0.100
OPT	==>	GFM	-0.267	-0.252	0.178	0.158
OPT	==>	SFM	-0.142	-0.132	0.174	0.450
PES	==>	GFM	0.564	0.532	0.171	0.002
PES	==>	SFM	0.524	0.485	0.164	0.003
PES	==>	GGM	0.186	0.177	0.171	0.299
PES	==>	SGM	0.091	0.086	0.158	0.586

Note: Factors are labeled: GGM= General Growth Mindset, SGM= Self Growth Mindset, GFM= General Fixed Mindset, SFM= Self Fixed Mindset, OPT= Optimism, PES=Pessimism. Items are labeled: ITIG = Implicit Theories of Intelligence Scale (ITI-General), ITIS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LOTR = Life Orientation Test-Revised (LOT-R). R=reverse coded item. R=reverse coded. S.E. is the standard error. P is significance level.

We note that the full measurement model used in phase one and structural model 2 are equivalent models, so the overall model fit is identical. There are numerous equivalent models we could have fit, but model 2 was considered because of its relationship to model 1 and its inclusion of crossed paths. Although overall model fit was equivalent for the full measurement model and model 2, there were meaningful differences in the fit of pathway. Model 2 was intended to provide explanation using pathways instead of correlations and serves as a theoretical comparison to model 1, not just an improvement over the fit of measurement model. All correlations among factors were significant in the measurement model but only six of the eight direct paths that replaced correlations in model 2 were significant in structural model 2.

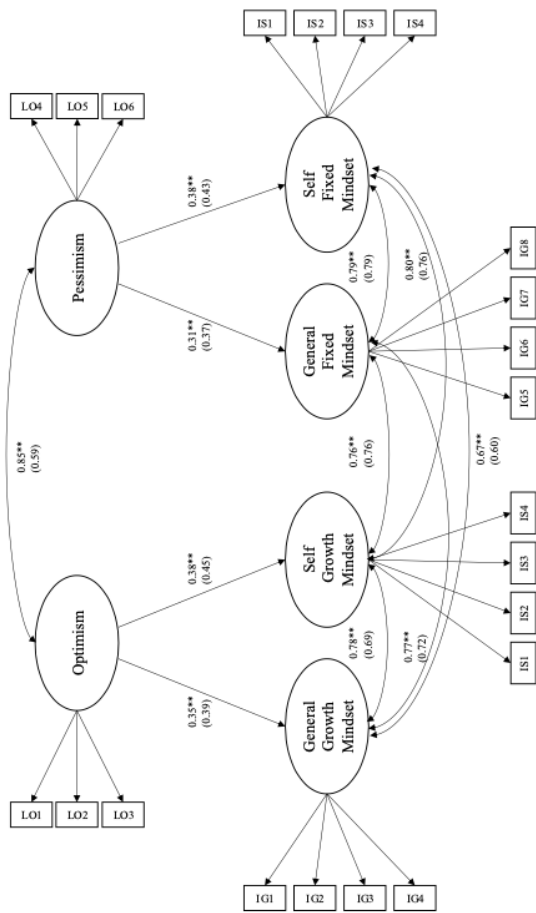


Figure 4. Structural Model 1 - optimism and pessimism uncrossed. ** designates significant standardized pathway at $p < .001$, * indicates pathway significant at $p < .01$ with unstandardized estimate in parentheses. Includes direct effects from optimism to growth mindset factors and from pessimism to fixed mindset factors. Correlations are modeled between optimism and pessimism and separately amongst the four mindset factors. All standardized and unstandardized loadings are presented in table 10. IG = Implicit Theories of Intelligence Scale (ITI-General), IS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LO = Life Orientation Test-Revised (LOT-R).

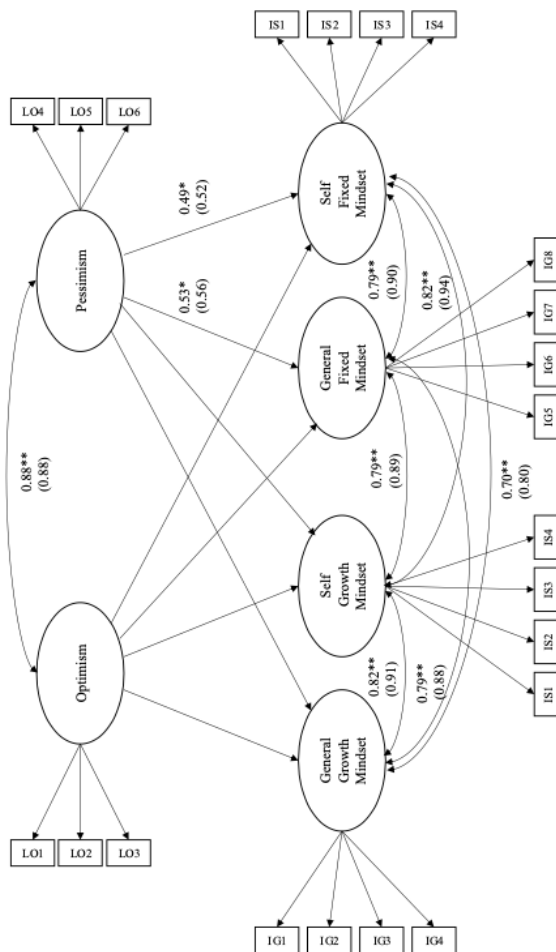


Figure 5. Structural Model 2- optimism and pessimism fully crossed. Includes direct effects from optimism and pessimism to all four mindset factors. Correlations are modeled between optimism and pessimism and amongst the four mindset factors. ** designates significant standardized pathway at $p < .001$, * indicates pathway significant at $p < .01$ with unstandardized estimate in parentheses. All standardized and unstandardized loadings are presented in table 11. IG = Implicit Theories of Intelligence Scale (ITI-General), IS = Revised Implicit Theories of Intelligence Scale (ITI-Self), LO = Life Orientation Test-Revised (LOT-R)

DISCUSSION AND CONCLUSIONS

These pilot data represent the first empirical evidence (to our knowledge) that optimism and pessimism influence factors implicated in growth and fixed mindset. These findings are critical to illuminate the complex contributing factors in the development of mindset, as well as targets for potential intervention. It may be that interventions designed to increase growth mindset (e.g., Paunesku et al., 2015) would have greater effects if they were targeted toward increasing optimism, as optimism impacts growth mindset. There is distinct research-supported evidence that optimism is a malleable trait (e.g., Peters, Flink, Boersman, & Linton, 2010), and the current findings provide a research-based rationale (in addition to a theoretical one) for the potential of changing mindset via changing optimism. It may be that optimism interventions are as effective or more effective than current mindset interventions, or perhaps that the addition of optimism interventions to current mindset interventions may increase the effects on target outcomes of mindset, academic achievement, motivation, etc.

Limitations

We are cautious in jumping from a mathematical indication of causality or direct pathway relationships in a path model to a logical one. Several limitations should be noted before we proclaim a robust causative relationship between optimism and mindset. Our data were collected at one university via a self-report survey. The sample size, although a reasonable size for pilot psychological research and supported by good measurement within each scale, had a low response rate. Self-selection bias could impact the study beyond measurement issues. It would be interesting to observe if these findings held over several trials. The findings should be explored in other populations (e.g., secondary students) with survey data as well as other indicators for the underlying factors when possible. It could also be the case that additional latent factor(s) exist that are currently undetected but that underlie all of the constructs in our model and would require further investigation to uncover. Although our data are not perfect, our findings warrant additional substantiation and investigation.

Scales, Factors and Models

Scales. All three scales (LOT-R, ITI-General and ITI-Self) demonstrated excellent performance on internal consistency for all measures. Further exploration of scales and subscales showed means (endorsement or average scores) with standard deviations that were comparable. Items individually discriminated well as seen by correlation of items with total

scores. The items as univariate measures of their individual scales performed as expected and were quality indicators for underlying factors. These data indicate that all of these scales performed well with our university student sample, and this provides the first data validating the use of the ITI-Self with college students.

Evidence for self-theory of intelligence factor. Our results provide support for findings by De Castella and Byrne (2015), suggesting that there is a self-growth mindset factor and a self-fixed mindset factor, both of which are distinct from the general growth and fixed mindset factors. This finding has important implications for researchers and interventionists as they develop assessments of mindset to measure baseline self-mindset and responses to interventions. Prior mindset research has provided clear evidence that *general* implicit theories of intelligence are linked to academic achievement and motivation, advanced course enrollment and higher grades (Blackwell et al., 2007; Paunesku et al., 2015). However, De Castella and Byrne (2015) found that a student's *self-theory* mindset was even more predictive of achievement and motivation than was their general mindset, so it will be important for researchers and practitioners to consider the use of the ITI-Self when one's self-theory and personal achievement and motivation are variables of interest. Thus, in first year programs, student affairs initiatives, or other similar programmatic university-based efforts, the ITI-Self is a reliable way in which to measure university students' orientations toward their own personal growth or fixed mindsets.

Four-factor model of mindset. The confirmatory models displayed superior model fit for the four-factor model for all 16 mindset items; this model had much better fit than the higher-order model (with four factors plus a general higher order mindset factor). That is, in this study we found evidence of four distinct mindset orientations: general growth, general fixed, self-growth, and self-fixed mindsets. This supports findings by De Castella and Byrne (2015) in which they found small but statistically significant differences on the original ITI Scale vs. the Revised ITI scale, indicating that students more strongly endorsed a fixed mindset when considering the malleability of others' intelligence as compared to the malleability of their own intelligence ($d=.17$). However, the higher order one factor model - suggesting a singular mindset orientation - may still hold interest for future research, given it had reasonable model fit. Future modeling research may investigate the utility of conceptualizing "mindset" as a continuum from very fixed to highly growth oriented.

Model fit. It is also worth noting here that utilizing methods such as those in MLSB, when raw data are available, that account for impacts of model fit measures can improve decisions around models. For example, De Castella and Byrne's (2015) analyses and discussion indicated that the Revised ITI scale is useful. However, we wanted to evaluate the indicators, considering their model fit was better for the two-factor model, but RMSEA criteria of .08 was only met for the two-factor model on the Revised ITI scale, and not met for the original ITI scale. This did not cause us to question if the competing two factor model was superior; it clearly was the more appropriate model based on all incremental model fit indices. What we did question, however, was the absolute measure of good fit since RMSEA was in a range that was neither good nor bad. Because of this we were unable to assert that there was relatively good fit between the hypothesized model and the observed data (Hu & Bentler, 1999). Therefore, although there was evidence that the scale was useful, the model fit warranted additional evaluation utilizing the methods we used in the present study. Practitioners often find themselves with polytomous ordinal data that could be analyzed with Satorra and Bentler (1994) adjustments, but obviously other issues such as missing data may impact the decision of which estimation method to use.

Additionally, our models accounted for non-normality which is too commonly ignored in Likert and polytomous scaling data. This oversight often leaves researchers with interesting models that do not have good data-model fit according to indices. Such was the case with De Castella and Byrne (2015) where RMSEA was not below .08 for any model. However, if one is able to correctly account for this issue in the data with adjustments such as those proposed by Satorra and Bentler (1994), we are likely to find that this and many other models have adequate data-model fit. In many cases, adjustments are not possible because the item level data is required, not just the covariance matrix, and missing data may require full information maximum likelihood estimation. It is particularly important to consider the use of these advanced analyses in the measurement of psychological data to provide a more accurate and nuanced understanding of psychological constructs and their measurement.

Structure of Optimism and Growth Mindset

Finally, our piloted structural model using optimism and pessimism as separate factors had better fit for parsimony when pathways were permitted only between optimism to growth mindset factors and pessimism to fixed mindset factors. This model may help to explain the two factors in each mindset scale. Growth mindset is driven by an underlying optimistic stance, and fixed mindset is influenced by a pessimistic one. The fully crossed model

(which allowed paths from optimism and pessimism to all of the growth and fixed items) fit as well as the uncrossed model, but was not an improvement on model fit indices, and with closer inspection of the pathways it became clear why that was the case. The crossed paths of optimism to fixed mindset and pessimism to growth mindset were *not* statistically significant, meaning those paths could be removed from the model. In removing those paths, it reduced us to Model 1, our original theoretically driven uncrossed model. This suggests not only that optimism and pessimism are clearly dissociable constructs, but that each provides a unique contribution to growth and fixed mindsets. Given the limitations of this pilot study, we do not discuss relationships as causal and caution on generalizing these findings until additional studies have been conducted.

IMPLICATIONS

Future Research

The findings of the present study establish a relationship in our data from optimism and pessimism to growth and fixed factors, respectively. Students demonstrate an increase in growth mindset when they have higher levels of optimism, and increased fixed mindset when they demonstrate higher levels of pessimism. The crossed effect was not significant, but may warrant additional consideration. For example, in model 2, there may well be crossed effects from optimism to fixed mindset and pessimism to growth mindset which may be potentially detected in a more powerful study. Future research will clarify these relationships.

Our results could suggest particular intervention targets to either increase growth mindset or decrease fixed mindset. Perhaps rather than or in addition to intervening to teach growth mindset, interventions should also be explicitly targeting a reduction in pessimistic thinking to weaken fixed mindset orientations and targeting improved optimistic thinking to build growth mindset. Additional research with adjusted mindset intervention targets will help clarify the effect magnitude of optimism and pessimism on mindsets.

Our results and theoretical framework indicate the use of two factors for each scale. We should caution it is possible that even though our model fit indicated two distinct factors for each scale that one factor model could still be appropriate. In future research we intend to explore tests of parallelism to determine if factors are distinct or just artifacts based on positively and negatively worded items. Negatively worded items can give rise to potential artifacts and bias in the data but also can indicate actual distinct factors regardless of the researcher's intent. However, even if some method or artifact

factors are present within a scale, the main focus of our pilot research provides the first starting point for relationships among mindset factors and optimism/pessimism.

Furthermore, the effects of mindset interventions can be short-lived and mindsets may return to pre-intervention levels in a matter of weeks (see Orosz, Péter-Szarka, Bóthe, Tóth-Király, & Berger, 2017). Would intervening on optimism as a driver of mindset result in more permanent and longer-lasting effects? Future research is needed to clarify this potential relationship. Finally, when interventions are implemented and multiple samples can be collected, causality may be explored for the types of models used in this study as well as the reversed causality model(s) where pathways are turned around and mindset predicts optimism and pessimism. This type of investigation would help us understand the flow of relationships in more detail.

Conclusion

In conceptualizing this study, we were curious to understand how one's optimism and/or pessimism – that is one's *expectation* of positive or negative future experiences – might shape his or her mindset toward expecting to improve intelligence (an optimistic expectation) or being unable to improve intelligence regardless of effort (a pessimistic expectation). We speculated that optimism is a broader expectation than mindset, and that this expectation of positive or negative future events might be a higher order factor in shaping one's mindset expectations. Thus, to explore this hypothesis, we modeled the relationship between optimism (and pessimism when we found evidence of the two-factor model) and fixed and growth mindsets. We found clear evidence that optimism and pessimism are implicated in growth and fixed mindset.

The concept of growth mindset has become a central focus in education research, and a number of interventions and programs have been developed to help educators teach growth mindset to students. The findings of the present study suggest that optimism interventions may well be an important target for these types of nonacademic intervention programs. Optimism is malleable and has been implicated in overall better school adjustment. This study offers additional evidence of its importance to educational outcomes since our results suggest a strong relationship between optimism and mindset.

REFERENCES

- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716-723.
- Baird, G. L., Scott, W. D., Dearing, E., & Hamill, S. K. (2009). Cognitive self-regulation in youth with and without learning disabilities: Academic self-efficacy, theories of intelligence, learning vs. performance goal preferences, and effort attributions. *Journal of Social and Clinical Psychology*, *28*(7), 881-908. doi: 10.1521/jscp.2009.28.7.881
- Berdik, C. (2013). *Mind over mind: The surprising power of expectations*. New York: Penguin Group.
- Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development*, *78*(1), 246-263. doi: 10.1111/j.1467-8624.2007.00995.x
- Boman, P., Smith, D. C., & Curtis, D. (2003). Effects of pessimism and explanatory style on the development of anger in children. *School Psychology International*, *24*, 80-94.
- Boman, P. & Yates, G. C. R. (2001). Optimism, hostility, and adjustment in the first year of high school. *British Journal of Educational Psychology*, *71*, 401-411.
- Buchanan, G., & Seligman, M. E. P. (Eds.). (1995). *Explanatory style*. Hillsdale, NJ: Erlbaum.
- De Castella, K., & Byrne, D. (2015). My intelligence may be more malleable than yours: The revised implicit theories of intelligence (self-theory) scale is a better predictor of achievement, motivation, and student disengagement. *European Journal of Psychology of Education*, *30*(3), 245-267. doi: 10.1007/s10212-015-0244-y
- Duckworth, A. L., & Eskreis-Winkler, L. (2013). True grit. *The Observer*, *26*(4), 1-3.
- Dweck, C. S. (2000). *Self-theories: Their role in motivation, personality, and development*. Philadelphia, PA: Psychology Press.
- ESSA (2015). Every Student Succeeds Act of 2015. Pub. L. No. 114-95 § 114 Stat. 1177 (2015-2016).
- Gal, E., & Szamoskovi, S. (2016). The association between implicit theories of intelligence and affective states – a meta-analysis. *Transylvanian Journal of Psychology*, *17*, 45-70. Retrieved from <http://search.proquest.com/openview/cce404ae85c51e1e1da0d72bf4942cae/1?pq-origsite=gscholar&cbl=2035941>
- Gustems-Carnicer, J., Calderón, C., & Santacana, M. F. (2017). Psychometric properties of the Life Orientation Test (LOT-R) and its relationship with psychological well-being and academic progress in college students. *Revista Latinoamericana de Psicología*, *49*(1), 19-27. <https://doi.org/10.1016/j.rlp.2016.05.001>

- Harris, P. (1996). Sufficient grounds for optimism? The relationship between perceived controllability and optimistic bias. *Journal of Social and Clinical Psychology, 15*, 9-52. doi: 10.1521/jscp.1996.15.1.9
- Hirsch, J. K., Britton, P.C., & Conner, K. (2009). Psychometric evaluation of the Life Orientation Test-Revised in treated opiate dependent individuals. *International Journal of Mental Health Addiction, 8*, 423-431. doi: 10/1007/s11469-009-9224-2
- Hu, L. & Bentler, P. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, *Structural Equation Modeling, 6*(1), 1-55.
- Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*, 424–453.
- Hu, L., & Bentler, P. (1995). Evaluation model fit. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (76–99). Thousand Oaks, CA: Sage.
- Jöreskog, K.G. (1993). Latent variable modeling with ordinal variables. In K. Haagen, D. J. Bartholomew, & M. Deistler (Eds.), *Statistical modelling and latent variables* (163–171). Amsterdam: Elsevier.
- Kline, R.B. (2011). *Principles and practice of structural equation modelling*. (3rd. Ed.). New York: Guilford Press.
- Lee, S.Y., Poon, W.Y., & Bentler, P.M. (1990). A three stage estimation procedure for structural equation models with polytomous variables. *Psychometrika, 49*, 115–132.
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*, 130-149.
- Muthén, B., & Kaplan, D. (1992). A comparison of some methodologies for the factor analysis of non-normal likert variables: A note on the size of the model. *British Journal of Mathematical Statistical Psychology, 45*, 19–30.
- Muthén, B. O. (1993). Goodness of fit with categorical and other nonnormal variables. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (205–234). Newbury Park, CA: Sage.
- Muthén B. & Kaplan D. (1985). A comparison of some methodologies for the factor analysis of nonnormal likert variables. *British Journal of Mathematical Statistical Psychology, 38*, 171–189.
- Orosz, G., Péter-Szarka, S., Bóthe, B., Tóth-Király, I., & Berger, R. (2017). How not to do a mindset intervention: Learning from a mindset intervention among students with good grades. *Frontiers in Psychology, 8* (311), 1-11. <http://doi.org/10.3389/fpsyg.2017.00311>
- Ottati, F. & Noronham, A. P. P. (2017). Factor structure of the Life Orientation Test –Revised (LOT-R). *Acta Colombiana de Psicología, 20*, 32-39. doi: 10.14718/ACP.2017.20.1.3
- Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic

- underachievement. *Psychological Science*, 26(6), 1-10. doi: 10.1177/0956797615571017
- Romero, C., Master, A., Paunesku, D., Dweck, C. S., & Gross, J. J. (2014). Academic and emotional functioning in middle school: The role of implicit theories. *Emotion*, 14(2), 227. doi: 10.1037/a0035490
- SAS Institute Inc. 2016. SAS/STAT® 14.2 User's Guide. Cary, NC: SAS Institute Inc.
- Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), *Latent variables analysis: Applications for developmental research* (399–419). Thousand Oaks, CA: Sage.
- Savalei, V. (2014). Understanding robust corrections in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 21(1), 149-160.
- Scheier, M. F., & Carver, C. S. (1985). Optimism, coping, and health: Assessment and implications of generalized outcome expectancies. *Health Psychology*, 4(3), 219–247. doi: 10.1037/0278-6133.4.3.219
- Scheier, M. F., & Carver, C. S. (1992). Effects of optimism on psychological and physical well-being: Theoretical overview and empirical update. *Cognitive Therapy and Research*, 16, 201-228.
- Scheier, M. F., Carver, C. S., & Bridges, M. W. (1994). Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A reevaluation of the Life Orientation Test. *Journal of Personality and Social Psychology*, 67(6), 1063 - 1078. doi: 10.1037/0022-3514.67.6.1063
- Schroder, H. S., Dawood, S., Yalch, M. M., Donnellan, M. B., & Moser, J. S. (2015). The role of implicit theories in mental health symptoms, emotion regulation, and hypothetical treatment choices in college students. *Cognitive Therapy and Research*, 39, 120-139. doi: 10.1007/s10608-014-9652-6
- Simsek, G. & Noyan, F. (2012) Structural equation modeling with ordinal variables: A large sample case study. *Quality & Quantity*, 46, 1571–1581.
- Tetzner, J., & Becker, M. (2017). Think positive? Examining the impact of optimism on academic achievement in early adolescents. *Journal of Personality*. Advance online publication. doi: 10.1111/jopy.12312
- Tuckwiller, B., Dardick, W. R., & Kutscher, E. L. (2017). Profiles of and correlations among mindset, grit, and optimism in adolescents with learning disabilities: A pilot study. *Journal of Interdisciplinary Studies in Education*, 6(1), 43-62.
- Vautier, S. Raufaste, E., & Cariou, M. (2003). Dimensionality of the revised Life Orientation Test and the status of the filler items. *International Journal of Psychology*, 38, 390-400.
- Yeager, D. S., & Dweck, C. S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist*, 47(4), 302-314. doi: 10.1080/00461520.2012.722805
- Yeager, D. S., Johnson, R., Spitzer, B. J., Trzesniewski, K. H., Powers, J., & Dweck, C. S. (2014). The far-reaching effects of believing people can change: Implicit theories of personality shape stress, health, and achievement during

adolescence. *Journal of Personality and Social Psychology*, 106(6), 867-884. doi: 10.1037/a0036335

Yeager, D. S., Trzesniewski, K. H., & Dweck, C. S. (2013). An implicit theories of personality intervention reduces adolescent aggression in response to victimization and exclusion. *Child Development*, 84(3), 970-988. doi: 10.1111/cdev.12003

WILLIAM R. DARDICK, PhD, is an Assistant Professor of Educational Research in the Assessment, Testing, and Measurement program, George Washington University, Washington, DC, USA. His major research interests include understating model fit across latent, emergent and manifest models, the novel uses of assessment and measurement theory, and simulation methods.

E-mail: wdardick@email.gwu.edu

ELIZABETH D. TUCKWILLER, PhD, is an Assistant Professor of Special Education and Disability Studies, George Washington University, Washington, DC, USA. Her major research interests include the measurement and role of nonacademic variables in teaching and learning, and the structure and facilitation of educational well-being. E-mail: btuckwiller@email.gwu.edu

Manuscript submitted: December 26, 2018

Manuscript revised: May 1, 2019

Accepted for publication: July 8, 2019
