A Mediation Model of Profiles of Motivational Regulation Strategies for Academic Tasks

Kim T. Trang
University of Kansas

Qianqian Pan
The University of Hong Kong

David M. Hansen
University of Kansas

Motivational regulation strategies are methods used to manage motivation levels. We used latent profile analysis to investigate strategy combinations and structural equation modeling to investigate how strategy profiles were related to achievement. Confirmatory factor analyses showed an eight-factor model was a good fit for the data and overall small to moderate correlations with metacognitive strategies and self-efficacy. Moreover, a three-profile solution provided the best fit for the data, differentiating among low, medium, and high usage of strategies. Results showed metacognitive strategies and self-efficacy fully mediated the relations between strategy profiles and achievement. Implications for education and management are discussed.

Keywords: motivational regulation, self-regulated learning, mediation analysis, latent profiles, academic achievement

INTRODUCTION

Motivation is essential for learning and performance. Research demonstrates, and educators know, that motivated students are more likely to expend effort on tasks, persist through learning difficulties, and achieve higher performance (Eccles, Wigfield, & Schiefele, 1998; Pintrich, 2003). Similarly, in the field of management, motivation is considered a crucial element in human development and human resource management (Muscalu & Muntean, 2013; Steers, Mowday, & Shapiro 2004). Decades of research on goal-setting theory show setting difficult, specific goals lead to higher performance (Locke & Latham, 2006). Research on work motivation theory has also shown how personal intentions, individual differences, and self-efficacy affect performance (Steers et al., 2004). In today's academic and work environments, students and employees are given more opportunities for independent learning and working with the rise in online learning and remote work environments. These structural changes require a fundamental change in the way individuals manage their learning and work processes for effective performance. In other words, it changes the way we think about how individuals motivate themselves.

Historically, motivation has been conceptualized as a static variable, from Maslow's theory of hierarchy of needs (Maslow, 1943) to expectancy-value theory (Eccles et al., 1998), as well as other work motivation theories (Van den Broeck, Carini, & Diefendorff, 2019). Motivation for learning and performance, however, fluctuates, creating challenges for performance. Individuals encounter daily motivational barriers, such as a lack of interest in the task or subject matter, making it difficult to maintain motivation for accomplishing goals. While managers, educators, and parents can create conditions conducive to motivation for learning and working, ultimately, individuals need to develop the ability to regulate their own motivation and overcome motivational barriers. Developing motivational regulation competency, then, is an important component for sustained learning and goal achievement in the 21st century.

LITERATURE REVIEW

Motivational Regulation Theory and Research

The field of motivation, like other areas in academia, builds on past models and frameworks. Early developments of motivation theory focus on instincts, drives, and other biological processes that influence behavior (Steers et al., 2004). Cognitive models and processes, however, came to dominate and influence many current theories, including goal-setting, self-regulation, and self-determination theory (Van den Broeck et al., 2019). There are several lines of inquiry into motivational regulation stemming from different research traditions (Boekaerts, 1996; Kuhl & Kraska, 1989; Pintrich, 2004; Sansone & Thoman, 2005; Wolters, 2003). For example, the achievement goal framework divided goals into performance and mastery, which are sources of motivation by providing direction for behavior (Elliot, 1999); individuals' persistence and performance can be explained by their beliefs about future performance (expectancy) and beliefs about the importance of the task (value) (Wigfield & Eccles, 2000); the degree of interest is another motivator and individuals can increase their interest to reach a goal (Krapp, 2002; Sansone & Thoman, 2005). In addition, goal theory suggests that setting short-term, concrete goals promote self-regulation and self-efficacy (Locke & Latham, 2002). Empirical research has demonstrated the importance of using effective strategies for regulating motivation. There have been studies on strategies related to environmental structuring (Zimmerman & Martinez-Pons, 1990), interest enhancement (Sansone & Thoman, 2005), self-efficacy enhancement (McCann & Garcia, 1999), and defensive pessimism (Norem & Illingworth, 1993). In general, these studies link motivational regulation strategies to positive outcomes, high performance, and achievement.

For this study, we used the framework advanced by Wolters and his colleagues (2003; 2011). The framework combines research from different areas and conceptualizes motivation as a self-regulatory process. Motivational regulation is defined as the ability to manage or direct one's motivation, and it involves the intentional use of thoughts and actions to influence one's motivation in order to accomplish a goal (Wolters, 2003). Although there are three dimensions of motivational regulation within this framework—metamotivational knowledge, motivational monitoring, and motivational regulation strategies—the focus here is on strategies because previous studies have shown direct associations between strategies and outcomes. *Motivational regulation strategies* are plans or methods by which individuals can actively monitor and manage their motivation levels. Emprical research has shown associations to motivational beliefs (Chow, 2011; Wolters & Benzon, 2013), cognitive strategies (Wang, 2013), procrastination (Kim, Brady, & Wolters, 2018), and academic achievement (Schwinger, Steinmayr, & Spinath, 2009). In other words, individuals who use strategies to regulate their motivation are more likely to possess positive beliefs about their abilities, use other types of cognitive strategies, achieve higher academically, and less likely to procrastinate.

Overall, in the past decade, much progress has been made to understand how individuals can directly affect their motivational states and the impact on outcomes. In conjunction with theoretical work was empirical work on how to measure motivational regulation strategies. To date, however, the literature is still sparse, and most studies have relied on a variable-centered approach, instead of a person-centered approach. The latter approach provides researchers with the opportunity to see how strategies may interact and how those interactions relate to relevant outcomes. The aims of the present study were (1) to evaluate reliability and validity evidence for a revised measure of motivational regulation strategies, (2) to investigate how strategies can be grouped into distinct profiles or patterns of usage, and (3) to explore mediating factors between profiles of motivational regulation strategies and academic achievement. The background literature for these aims are reviewed below.

Measuring Motivational Regulation Strategies

Initial work on a measure for motivational regulation strategies came from Wolters and colleagues (1999). The original English version had five strategies (Wolters, 1999) which got further developed into six (Wolters & Benzon, 2013). Additional psychometric work on the measure included an eight-dimensional, German version (Schwinger et al., 2009) and a six-dimensional, Chinese version (Wang, 2013). Overall, findings from these studies provided evidence for multi-dimensionality: the construct of motivational regulation strategies has different dimensions, each strategy measuring a different aspect of the ability to regulate motivation. For example, a strategy focused on increasing the value of an academic task is different from a strategy focused on using rewards. Recently, a brief version of regulation of motivation scale was developed and evaluated (Kim et al., 2018). Results showed two factors emerged: regulation of motivation and willpower. Regulation of motivation was interpreted as an overall assessment of students' general beliefs about engaging in the regulation of motivation, rather than the use of specific strategies. As shown, the current literature is sparse, and further validation research needs to be conducted, focusing on integrating previous studies and evaluating more evidence for the instrument.

In this study, we build on the existing work by testing a revised measure that includes strategies from all versions. We looked at strategies from the six-dimensional English version (Wolters & Benzon, 2013), eight-dimensional German version (Schwinger et al., 2009), and six-dimensional Chinese version (Wang, 2013). There are strategies that have not been tested or confirmed on the English version, including proximal goal setting and efficacy enhancement strategies. Thus, there is a need to re-evaluate these items and determine if they also appear as distinct factors using an English-speaking sample. The first goal of the study, then, was to investigate the reliability and validity evidence for a revised measure of motivational regulation strategies. We assessed the internal structure of the measure as well as looked at how strategies are linked to other variables, including procrastination, self-efficacy, and academic achievement.

Individual Differences in Motivational Regulation Strategies

In general, studies on motivational regulation strategies have taken a variable-centered approach, instead of a person-centered approach. The latter is rooted in a holistic-interactionist view on individual development (Bergman & Andersson, 2010). The focus of interest is on individuals and their patterns of development, considering how domains are connected. To date, only a few studies have taken a person-centered approach to investigate motivational regulation strategies. For the few studies that have, latent profile analysis (LPA) was used as a method of investigation. LPA is a person-centered statistical analysis used to identify subgroups (latent profiles) based on unobserved constructs. This method has become one of the common modeling techniques in educational and psychological research to explore unobserved homogeneous subgroups (Marsh, Lüdtke, Trautwein, & Morin, 2009).

In one study, Schwinger and colleagues (2012) used LPA to look at different motivational regulation profiles and their relations to academic achievement and effort. Results showed five motivational regulation strategies profiles: *low* and *high* frequency of strategies usage profiles; a *goal-focused* profile consisting of higher scores for goal-oriented self-talk strategies; an interest-focused profile with higher scores on interest enhancement strategies; and a *performance self*-talk profile consisting of higher scores on the performance self-talk strategy. In addition, results suggested that students who reported high usage of motivational regulation strategies overall tended to put more effort into their studies. High-usage profile students also reported better grades compared to students with a performance self-talk profile. More recently, using LPA, Reindl and colleagues (2020) looked at profiles of motivational and emotional regulation strategies. They found a three-profile solution was the best fit for the data: *goal-directed* *learners* had high levels of adaptive strategies and performance-approach self-talk and low rumination; *worried performers* had low adaptive strategies and high performance-approach self-talk and rumination; and *inhibited ruminators* had low use of learning strategies. In general, students with the goal-directed profile had the most adaptive performance in terms of using other learning strategies. Overall, these two studies provided some evidence of individual differences in patterns of motivational regulation strategies usage and these patterns were linked to academic and learning outcomes.

More research, however, needs to be conducted to replicate and expand on existing work. LPA provides a nuanced view of the construct by revealing individual differences in how individuals use motivational regulation strategies. In this study, we used LPA to investigate whether different patterns or profiles emerged from the data and how the profiles may be related to performance outcomes.

Motivational Regulation Strategies and Other Variables

In building validity evidence for a measure, the *Standards for Educational and Psychological Testing* (2014) views validity as a unitary concept, involving many types of evidence, and validation of a measure requires evaluating claims. Below, we review evidence in the literature for a measure of motivational regulation strategies based on evidence of relations to other variables. There is a large body of literature assessing the association between motivational regulation strategies and motivational beliefs, metacognitive strategies, and performance.

Relations to Motivational Beliefs and Metacognitive Strategies

Motivational regulation strategies are conceptually distinct from motivational beliefs, which are generally conceptualized as the cognitive aspect of motivation (e.g., achievement goals, task value). Previous studies provided evidence that motivational regulation strategies can be distinguished from motivational beliefs and epistemic beliefs (Chow, 2011; Wang, 2013; Wolters & Benzon, 2013). Results showed small to medium correlations between motivational regulation strategies and measures of self-efficacy, achievement goal orientation, and personal epistemology. These studies provided empirical evidence for the distinction between the motivational beliefs and motivational regulation, supporting Wolters's (2003) theory. Motivational regulation strategies are conscious and deliberate: learners are aware of factors that affect their motivation and they are able to directly shape their motivation. In contrast, most motivational belief theories do not make explicit assumptions about individuals' motivational awareness or motivational regulatory capabilities.

In addition, motivational regulation strategies are conceptually distinct from metacognitive strategies, although the two are related (Wolters, 2003). The function of motivational regulation strategies is to influence and enhance motivational states. In contrast, the function of metacognitive strategies is to influence and enhance cognitive processing. The two constructs, however, may share some associations because they are thought to be part of a larger self-regulatory system. Empirical studies supported a positive, small to medium, correlation between the two constructs (Kim et al., 2018; Wolters & Benzon, 2013; Wang, 2013). The correlations, however, were not large enough to suggest that the measures were assessing the same construct.

In sum, previous studies distinguished motivational regulation strategies from other constructs in the motivation and self-regulated learning literature. This distinction is important in building a validity argument for the measure, as well as supporting theory. In this study, we included measures of metacognitive strategies and self-efficacy to evaluate validity evidence based on relations to similar constructs.

Relations to Performance

Motivational regulation strategies have been linked to performance outcomes. Students who use motivational strategies were more likely to report a higher GPA (Wolters, 1999), effort (Schwinger et al., 2012), and pleasure/interest (Smit, Brabander, Boekaerts, & Martens, 2017). Students were also more likely to report less procrastination (Kim et al., 2018) and rumination (Reindl et al., 2020). The relations between motivational regulation strategies and performance, however, may not be direct. Several studies provided evidence that effort was a mediator in which students who used motivational regulation strategies were more likely to expend effort, which led to higher academic performance (Schwinger et al., 2009; Schwinger & Steinsmeier-Pelster, 2012). Recent research suggests procrastination may also be a mediator. One study showed procrastination mediated the relations between motivational regulation strategies and GPA and affective/cognitive well-being (Grunschel, Schwinger, Steinmayr, & Fries, 2016). Students who used motivational regulation strategies were less likely to procrastinate and had better GPAs and higher affective/cognitive well-being.

In sum, previous studies suggest the relations between motivational regulation strategies and performance is not direct. There may be mediating variables, such as effort and procrastination, that explains the relations between motivational regulation strategies and performance. In this study, we build on this base of evidence by investigating a mediating model whereby metacognitive strategies, self-efficacy, and procrastination were mediators between motivational regulation strategies and academic achievement.

The Current Study

The current study had three goals. The first goal was to obtain reliability and validity evidence for a revised measure of motivational regulation (MR) strategies. The MR strategies measure used in this study included a range of strategies assessed in previous studies. We made significant revisions to the original items to enhance clarity and added new items with the goal of improving conceptual representations of strategies. The second goal was to explore how individual students integrated the eight MR strategies differently, in other words, if there were different MR profiles representing distinct patterns of usage. The third goal was to test a mediation model whereby metacognitive strategies, college self-efficacy, and academic procrastination were mediators between MR profiles and academic achievement.

Hypothesis 1a. *The eight-factor model of MR strategies is the best fit for the data.*

Hypothesis 1b. *The MR strategies will be positively, small to medium, related to metacognitive strategies and college self-efficacy.*

Hypothesis 1c. *The MR strategies will be negatively related to academic procrastination and positively related to academic achievement.*

Hypothesis 2. *Participants integrate MR strategies differently, such that multiple MR profiles exist in the current sample.*

Hypothesis 3. *The MR strategies profiles will predict academic achievement through metacognitive strategies, college self-efficacy, and academic procrastination.*

METHOD

Participants

This study was reviewed by the institutional review board (IRB) of a Midwest, public university, where the study was conducted. Participants were undergraduate students (N = 800) recruited from a survey research pool (Qualtrics Panel) and were given a small monetary incentive for their participation. Participants were selected if they met the following criteria: age 18-25 and enrolled in a 2- or 4-year college. Participants (age range = 18-25, M = 21.44, SD = 2.22) were female (58.25%), Anglo-American (71.50%), African-American (12.50%), Hispanic (5.75%), Asian/Asian-American (5.75%), and Other race (4.50%). Students were also Freshmen (22.50%), Sophomore (25.63%), Junior (22.75%), Senior (25.38%), and Other (3.75%). Students studied in a variety of fields including business, education, mathematics, and psychology.

Measures

Demographics

Students were asked to report on basic demographics including age, race, gender, academic institution, major, class, and year in the program. Demographic variables were used as controls in the study.

Academic Achievement (GPA)

Grade Point Average (GPA) in the current study had higher values indicated higher academic achievement. Students were asked to report their current GPA, which ranged from 1.6 to 4.8 with a M = 3.4 and SD = .49.

Motivation Regulation Strategies

Preliminary, unpublished results conducted with an adapted 50-item measure with nine strategies showed a poor fit for a 9-factor model (authors, 2018). Based on these results we revised the measure by selecting 3-4 items for each strategy that had high loadings and substantively represented the strategy. These revisions resulted in a 32-item measure representing eight strategies: regulation of value (ω = .76), regulation of performance goals (ω = .83), regulation of mastery goals (ω = .79), self-consequating (ω = .80), environmental structuring (ω = .77), regulation of situational interest (ω = .77), efficacy self-talk (ω = .79), and proximal goal setting (ω = .79). The items were on a scale from 1 = *Never* to 6 = *All of the Time*. The scale is intended to measure how frequently students use different types of motivational regulation strategies. (Note: we used ω to report reliability because α is only appropriate when all item factor loadings are the same.)

Metacognitive Strategies Scale

The metacognitive strategies scale came from the Motivated Strategies for Learning Questionnaire measure (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991). Metacognitive strategies items measure students' ability to plan, monitor, and regulate their cognition (ω = .81). The original items referenced a specific course, so revisions were made to make it more general. A sample item from the metacognitive regulation scale is, "When studying I try to determine which concepts I don't understand well." There is a total of eight items measured on a 7-point Likert-scale from 1 = *Strongly Disagree* to 7 = *Strongly Agree*.

Academic Procrastination

Academic procrastination was measured using the Academic Procrastination Scale-Short Form (APS-S; Yockey, 2016). The APS-S (ω = .85) measures the frequency by which students put off projects, homework, or important deadlines. A sample item is, "I put off projects until the last minute." There is a total of five items, measured on a 5-point Likert-scale from 1 = *Strongly Disagree* to 7 = *Strongly Agree*.

College Self-efficacy

Self-efficacy for college coursework was measured using the College Self-Efficacy Inventory (CSEI; Barry & Finney, 2009). The CSEI (ω = .81) contains seven items measured on a scale from, 1 = *Strongly Disagree* to 7 = *Strongly Agree*.

Data Analysis

Reliability

Internal reliability was assessed using coefficient omega (Bollen, 1980; Raykov, 2001), which ranges from 0 to 1, higher omega values indicate higher reliability of the scale. As a general guideline, threshold values of .70 is the cutoff recommended for research purposes (Lance, Butts, & Michels, 2006).

Confirmatory Factor Analysis

To test the latent construct of motivational regulation strategy, which composed of eight lower-level factors (i.e., eight motivational regulation strategies) and a higher-level factor, the general motivational regulation factor, we followed the conventional two-step approach (Brown, 2006). First, separate single-factor confirmatory factor analysis (CFA) models were examined to assess model fit and reliability of each motivational regulation strategies subscale. This step helped us identify the potential misfit within one single-factor model. Only after the single-factor model achieved acceptable model fit, the higher-order structural could be considered. Robust maximum likelihood (MLR) was used as the estimator. Global model fit was evaluated using the root mean square error of approximation (RMSEA) and its 90% confidence interval, the comparative fit index (CFI), and the Tucker-Lewis index (TLI). Hu and Bentler's (1999) guidelines for acceptable model fit are RMSEA ($\leq$ .08), TLI ($\geq$ .90), and CFI ($\geq$ .90). Second, an overall model was estimated in which all eight factors were fitted simultaneously with covariances estimated freely among them. Each factor was identified by fixing the first item loading on each factor to one and each factor mean to zero and estimating the factor variances, item intercepts, item residual variances, and item loadings. Standardized factor loadings were also generated and reported. CFAs were estimated using *lavaan* in the programming environment R. Estimated latent factor scores were predicted via Bartlett using *lavPredict*. (Note: single-factor CFAs were also conducted for the metacognitive strategies, college self-efficacy, and academic procrastination scales.)

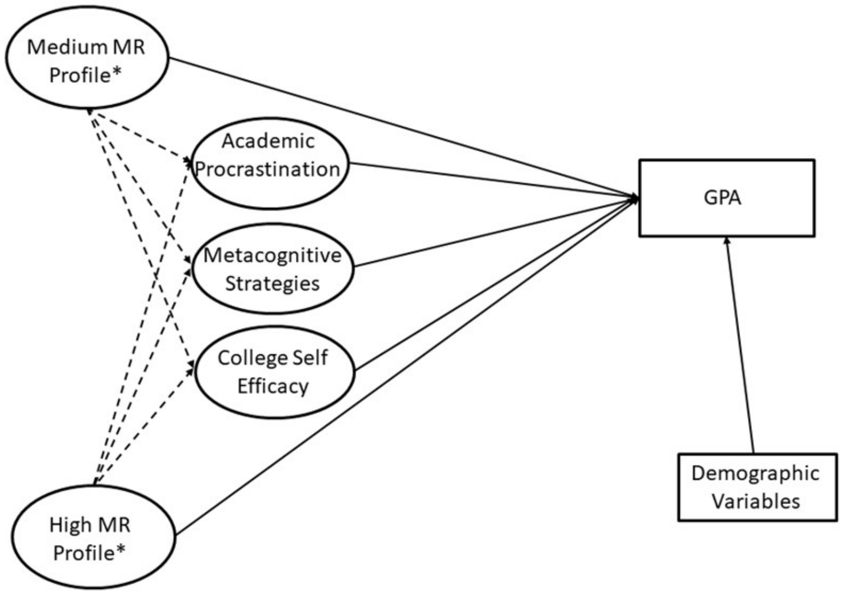
Latent Profile Analysis

Latent profile analysis (LPA) was used to classify participants into different MR strategies profiles. In the current study, latent factor scores of each MR strategy obtained from the CFA models were used as indicators. As an exploratory data analysis method, a series of LPAs were conducted, ranging from two up to five latent profiles. The final model was selected using three criteria, including the classification accuracy, model comparison test results, and theoretical interpretability of the profile structure. The classification accuracy was evaluated by using posterior probabilities (> .80) and the entropy value (entropy near one is desirable) (Wang & Wang, 2019). Bayesian information criteria (BIC) value, Lo, Mendell, and Rubin likelihood ratio test (LMR-LRT), and Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) were used to compare models and to determine the number of latent classes. The selected model is the one with the fewest number of latent profiles with the lowest BIC values and nonsignificant LMR-LRT and VLMR-LRT. The selected model was reviewed for theoretical interpretability. The expectation-maximization (EM) algorithm was used for parameter estimation and analyses were completed in *Mplus* version 7.4

Structural Equation Modeling

Structural Equation Model (SEM) was used to investigate the relations between motivational regulation strategies and academic achievement. We followed the two-staged procedure to examine mediation. First, the direct effect between participants' GPA and MR strategies profiles were examined. Then, a full SEM mediation model was estimated (see Figure 1), where metacognitive strategies, college self-efficacy, and academic procrastination were the mediators and the indirect effects between the GPA and mediators were also estimated. Full mediation was defined when the direct effect became nonsignificant after including the mediators. Partial mediation was defined when the direct effect remained a significant predictor in both models but was reduced and the indirect effects were significant in the full SEM mediation model. To improve the interpretability of the results, the participants' GPA was standardized before entering the model. SEMs were estimated using robust maximum likelihood (MLR), and the same fit criteria as CFAs were used to assess model fit.

FIGURE 1
FULL STRUCTURAL EQUATION MEDIATION MODEL



Note. Solid lines represent direct effects; dash lines represent indirect effects. *Low MR profile is the reference group.

Missing Data

The missing rate, calculated by the total of missing data points divided by the total data point, in the current sample was very low (around .23%). Before conducting CFA, the normality was checked using the skewness and kurtosis. Results found that a total of 24 items had skewness between -.5 and .5, considered as approximately symmetric, another 27 items had skewness between -1 to -.5 or between .5 and 1, considered as moderately skewed. Only one item had the skewness larger than 1. All items had kurtosis between -1.3 and .6, which was considered acceptable in order to prove normal distribution (George & Mallery, 2010). MLR was adopted to adjust for non-normality in the analysis.

RESULTS

Validity Evidence for Motivational Regulation Strategies Measure

First, we fitted single-factor CFAs to the data to assess the fit of each individual MR strategy subscale. Results showed all single-factor CFA models achieved a good model fit. In addition, all subscales had good internal reliability, $\omega > .75$, as shown in Table 1. Second, we fitted an eight-factor model to the data, and results showed good fit, $\chi2(436) = 1496.685$, $p < .01$, CFI = .903, TLI = .889, RMSEA = .059 (90% CI = .055–.062). In addition, item loadings and R-squared values showed high factor loadings (above .50) for all items, suggesting the items were good representation of the latent factors (see Table 2)

TABLE 1
SUBSCALE RELIABILITY AND LATENT FACTOR CORRELATIONS AMONG SUBSCALES

Subscale	ω	1	2	3	4	5	6	7	8	9	10	11	12
1. Regulation of value	.76	1											
2. Regulation of performance goals	.83	.53	1										
3. Regulation of mastery goals	.79	.67	.56	1									
4. Self-consequating	.81	.54	.53	.52	1								
5. Environmental structuring	.78	.48	.45	.58	.49	1							
6. Regulation of situational interest	.77	.69	.33	.63	.50	.52	1						
7. Efficacy self-talk	.79	.62	.52	.69	.58	.58	.64	1					
8. Proximal goal setting	.84	.55	.52	.59	.57	.57	.50	.59	1				
9. Metacognitive strategies	.85	.55	.52	.59	.53	.54	.50	.55	.56	1			
10. College self-efficacy	.81	.50	.46	.52	.40	.47	.42	.50	.47	.71	1		
11. Academic procrastination	.85	-.06^{+}	-.16	-.17	.01^{+}	-.10	.03^{+}	-.12	-.07^{+}	-.08	-.23	1	
12. Academic achievement	---	.10	.10	.10	.03^{+}	.07	.10	.06^{+}	.08	.07	-.14	.17	1
12. Academic achievement	---	.10	.10	.10	.03^{+}	.07	.10	.06^{+}	.08	.07	-.14	.17	1

Note. ω is the reliability index calculated based on the single-factor CFAs. +estimates are *not* significant at $p < .01$.

Table 1 displays the correlations among latent factor scores of subscales among MR strategies and metacognitive strategies, college self-efficacy, academic procrastination, and academic achievement. Correlations (p < .01) among MR strategies were medium to large (range = .48–.69) and in the positive direction, suggesting that each subscale shared a common latent construct, but they were not large enough to suggest a lack of distinction among strategies. In addition, results indicated medium correlations (p < .01) between MR strategies and metacognitive strategies and college self-efficacy, range = .40–.59. This provided validity evidence based on construct differentiation, i.e., the MR strategies measure was assessing strategies to regulate motivation and the metacognitive strategies scale was assessing strategies to regulate cognition.

Moreover, results showed small, but statistically significant correlations between MR strategies and academic procrastination and achievement. Academic procrastination was negatively correlated with four MR strategies: regulation of performance goals (r = -.16, p < .01), regulation of mastery goals (r = -.17, p < .01), environmental structuring (r = -.10, p < .01), and efficacy self-talk (r = -.12, p < .01). Academic achievement was positively correlated with six MR strategies: regulation of value (r = .10, p < .01), regulation of performance goals (r = .10, p < .01), regulation of mastery goals (r = .10, p < .01), environmental structuring (r = .07, p < .01), regulation of situational interest (r = .10, p < .01), and proximal goal setting (r = .08, p < .01). Overall, these results suggested the MR strategies may predict important academic outcomes, providing additional validity evidence supporting its psychometrics property.

TABLE 2
EIGHT-FACTOR MODEL STANDARDIZED FACTOR LOADINGS AND R-SQUARED

	Factor Loadings								R^2
	1	2	3	4	5	6	7	8	
Regulation of Value									
I relate the class material to what I want to do in life.	.58								.34
I try to see how knowing the material is personally relevant.	.68								.47
encompasses connect the class material with something I find interesting.	.69								.48
I tell myself that I will use the material later in life.	.69								.47
Regulation of Performance Goals									
I think about getting good grades (e.g., A, B).		.79							.62
I tell myself that I need to do well in this class.		.77							.59
I focus on the importance of getting good grades.		.73							.53
I tell myself that it's important to do well in this class.		.69							.47
Regulation of Mastery Goals									
I tell myself to keep working so I can learn as much as I can.			.71						.51
I persuade myself to keep at it to see how much I can learn.			.72						.52
I convince myself to work hard for the sake of learning.			.68						.47
I challenge myself to complete the work and learn as much as possible.			.69						.48
Self-Consequating									
I make a deal with myself that I can do something fun after I complete my work.				.72					.51
I promise myself a reward after I finish my work.				.71					.51
I promise myself I can do something I want later if I finish the assigned work now.				.78					.61
I tell myself I can do something I like later if I complete the work now.				.66					.43

Environmental Structuring					
I make sure I have as few distractions as possible.	.61				.37
I try to get rid of any distractions that are around me.	.74				.55
I change my surroundings so it's easy to concentrate on the work.	.67				.45
I try to anticipate distractions and set up my environment to avoid them.	.71				.50
Regulation of Situational Interest					
I imagine that the work is enjoyable to complete.		.68			.46
I try to see how doing the work can be fun.		.74			.54
I make a game out of completing the work.		.61			.37
I focus on features of the work that are fun.		.69			.47
Efficacy Self-Talk					
I tell myself, "You can do this!"			.70		.49
I tell myself that I'll be able to understand and remember the class material.			.69		.48
I tell myself that I'll be successful if I keep at it.			.72		.52
I tell myself, "You are doing a good job."			.64		.41
Proximal Goal Setting					
I set short-term goals for large tasks/projects.				.76	.58
I approach the class material one step at a time.				.67	.45
I break the class material into small chunks.				.71	.51
I set small, specific goals for each part of the task.				.67	.44

Note. Standardized factor loadings, all estimates are significant at $p < .01$.

Latent Profile Analysis of Motivational Regulation Strategies

The eight estimated latent factors scores were used as indicators in LPA to identify the latent profile membership of participants. Table 3 shows model comparison statistics for three LPA models. Results indicated the three-profile model fit significantly better than the two-profile model, while the four-profile model did not improve model fit over the three-profile model. In addition, the three-profile model had higher certainty in classification than the four-profile model as indicated by the higher entropy values. We labeled the three profiles into different levels of usage of MR strategies: low (29.75%), medium (48.38%), and high (21.87%). Overall, the results suggested there were three distinct MR strategies profiles presented in the data.

TABLE 3
LATENT PROFILE ANALYSIS FIT SUMMARY

Number of Profiles	Number of Parameters	Log-Likelihood	Sample-size Adjusted BIC	VLMR-LRT	LMR-LRT	Entropy
2	25	-6564.56	13217	59.245 (p <.001)	2322.976 (p <.001)	.888
3	34	-6228.6	12577	96.044 (p =.001)	660.92 (p =.001)	.857
4	43	-6079.48	12310	441.336 (p =.306)	293.372 (p =.310)	.854

Mediation Model of Motivational Regulation Strategies Profiles and Academic Achievement

We fitted single-factor CFAs to the metacognitive strategies, college self-efficacy, and academic procrastination scales. Results showed a good fit for each scale: metacognitive strategies: CFI = .965, TLI = .951, RMSEA = .057 (90% CI = .040–.075); college self-efficacy: CFI = .984, TLI = .971, RMSEA = .055 (90% CI = .032–.079); and academic procrastination: CFI = 1.000, TLI = 1.000, RMSEA = <.001

(90% CI = <.001–.034). These CFAs were included in the full mediation SEM. The SEM was used to examine if metacognitive strategies, college self-efficacy, and academic procrastination mediated the relations between MR strategies profiles and academic achievement.

Table 4 shows results from the full model with standardized Betas (β). The model demonstrated good fit: CFI = .917, TLI = .908, RMSEA = .040 (90% CI = .036–.044). There were four significant indirect effects: (1) Medium MR profile and metacognitive strategies, β = -.158, $p < .05$; (2) High MR profile and the metacognitive strategies, β = -.261, p < .05; (3) Medium MR profile and college self-efficacy, β = -.183, $p < .05$; and (4) High MR profile and college self-efficacy, β = .302, $p < .05$. In this model, there were no significant direct effects between MR profiles and GPA. Results also showed significant direct effects between GPA and two mediators: metacognitive strategies and college self-efficacy.

Overall, these results suggested that metacognitive strategies and college self-efficacy fully mediated the relations between MR profiles and GPA. There was, however, no evidence to support that academic procrastination was a mediator. There were only direct effects between MR profiles and academic procrastination and academic procrastination and GPA.

TABLE 4
FULL SEM MEDIATION MODEL

	β[1]	SE[2]	β[3]
Intercept	.119	.365	.120
Demographic → GPA			
Age	-.018	.017	-.040
Year	.030	.051	.038
Female	.086	.079	.042
African-American	-.231	.125	-.077
Hispanic	-.282	.166	-.066
Asian/Asian-American	-.094	.152	-.022
Other Race	-.031	.201	-.006
Sophomore	.087	.114	.039
Junior	-.038	.139	-.016
Senior	-.190	.170	-.008
Direct Effects			
Metacognitive Strategies → GPA	-.418	.186	-.320*
College Self-efficacy → GPA	.410	.133	.410*
Academic Procrastination → GPA	-.061	.027	-.096*
Medium MR Profile → GPA	.195	.105	.097
High MR Profile → GPA	.088	.160	.037
Medium MR Profile → Metacognitive Strategies	.756	.072	.492*
Medium MR Profile → College Self-efficacy	.895	.090	.447*
Medium MR Profile → Academic Procrastination	-.422	.122	-.134*
High MR Profile → Metacognitive Strategies	1.504	.106	.815*
High MR Profile → College Self-efficacy	1.774	.116	.737*
High MR Profile → Academic Procrastination	-.491	.191	-.129*
Indirect Effects			
Medium MR Profile * Metacognitive Strategies → GPA	-.316	.144	-.158*
Medium MR Profile * College Self-efficacy → GPA	.367	.122	.183*
Medium MR Profile * Academic Procrastination → GPA	.026	.014	.013

High MR Profile * Metacognitive Strategies → GPA	-.629	.283	-.261*
High MR Profile * College Self-efficacy → GPA	.727	.236	.302*
High MR Profile * Academic Procrastination→ GPA	.030	.018	.012

Note. *$p < .05$. MR = Motivational Regulation Strategies. GPA was standardized before entering the model. Low MR was the reference group for Medium MR and High MR profiles; Anglo-American was the reference group for race; freshman was the reference group for class. β^1 represents the unstandardized coefficients, SE^2 represents the standard error, and β3 represents the standardized coefficients.

DISCUSSION

Validity Evidence for Motivational Regulation Strategies Measure

The first goal of the study was to evaluate validity evidence for a revised measure of motivational regulation strategies. Findings showed overall high internal reliability and moderate correlations among subscales. In addition, confirmatory factor analyses showed the hypothesized eight-factor model was a good fit for the data, demonstrating multi-dimensionality of the construct. These findings extended and supported previous validation work on other versions of the measure (e.g., Schwinger et al., 2009, Wang, 2013) and provided validity evidence based on the internal structure of the measure. Moreover, findings also provided evidence for validity based on relations with other variables. The motivational regulation strategies correlated moderately with other constructs, metacognitive strategies and college self-efficacy as assessed by other measures, providing evidence based on construct discrimination. Furthermore, some motivational regulation strategies also correlated slightly with academic procrastination and GPA. These results are in line with the research literature linking motivational regulation strategies to academic outcomes (e.g., Schwinger et al., 2012).

Overall, in this study, we collected validity evidence for a revised measure of motivational regulation strategies. The findings provided evidence to support the validity of the eight-strategy measure based on internal structure, relations to similar constructs, and relations to outcomes. This contributes to the existing research base, suggesting that the revised measure is reliable and valid to study individuals' use of motivational regulation strategies. In a developing field, a well-established measure is important to move empirical and theoretical research forward. A particular focus of future studies would be to investigate the use of motivational regulation strategies in different samples (e.g., non-college students) and organizational contexts (e.g., businesses, non-profits). The importance of work motivation and focusing on actions that employees can implement have been highlighted in performance management models (DeNisi & Pritchard, 2006). Though managerial evaluation is important to provide feedback toward goal attainment (Lunenburg, 2011), it is increasingly important that individuals self-reflect and self-evaluate to adjust their motivation and actions. Self-reflection is a critical piece of self-regulated learning (Zimmerman et al. 2011) and will become increasingly necessary as we move toward more independent learning environments (e.g., online learning, remote work).

Profiles of Motivational Regulation Strategies and Academic Achievement

Profiles of Motivational Regulation Strategies

The second goal of the study was to investigate interactions among the strategies, that is, whether different patterns of usage could be identified. Results showed three distinct profiles, differentiated by the levels of usage: *low*, *medium*, and *high*. Profiles were classified as overall uniformly low, medium, or high strategy usage across all eight motivational regulation strategies. There were, however, some distinctions to point out. For the *low* profile group, there was a slightly lower usage of efficacy self-talk and proximal goal setting compared to other strategies. In contrast, for the *high* profile group, there was a slightly higher usage of efficacy self-talk and proximal goal setting. The *medium* profile group used all eight strategies at similar levels. This suggests efficacy self-talk and proximal goal setting may be strategies that differentiate subgroups of students. In previous work, Schwinger and colleagues (2012) found a distinct *goal-focused* profile which emphasized goal-oriented self-talk strategies, such as mastery self-talk and performance-approach self-talk. In this study, we found that efficacy self-talk may be a differentiator.

Overall, these findings suggest, using a revised eight-strategy measure of motivational regulation strategies, students can be classified into groups that use strategies at different levels. These profiles were similar to those reported in previous work and provided additional evidence for conceptualizing motivational regulation strategies along different profiles or patterns of usage. Conceptually, distinct motivational regulation strategies profiles may reflect how routinely individuals deploy strategies (Miele & Scholer, 2016), which contrasts with models that treat strategies as a single latent factor (Kim et al., 2018). Understanding individual differences in strategy usage and how they are connected to achievement and performance will inform interventions in the field. Interventions should focus on targeting distinct components of motivation because they will have different effects on engagement and behavior (Miele & Scholer, 2016). In other words, this means taking the time to understand unique motivational tendencies and behaviors. For example, if an employee is oriented toward efficacy self-talk, a manager might acknowledge and encourage that strategy by providing positive, encouraging words and space for self-expression. People are essential for organizations' development and performance, and focusing on motivation is a crucial element in human development (Muscalu & Muntean, 2013).

Meditating Factors Between Profiles of Motivational Regulation Strategies and Academic Achievement

The third goal of the study was to investigate the relations between profiles of motivational regulation strategies and academic achievement. Results showed metacognitive strategies and college self-efficacy were mediators between motivational regulation strategies profiles and academic achievement. Students who used motivational regulation strategies at medium and high levels, compared to low, were more likely to use metacognitive strategies and have high self-efficacy, which was then directly associated with their academic achievement. These results are similar to previous work (Schwinger & Steinsmeier-Pelster, 2012), but this study is the first to demonstrate that other self-regulated learning variables (metacognitive strategies and self-efficacy) served as mediators, in addition to effort.

The findings suggest a different mechanism by which motivational regulation strategies may impact academic achievement. The research literature has demonstrated positive associations between motivational regulation strategies and metacognitive strategies and self-efficacy (Kim et al., 2018; Wang, 2013; Wolters & Benzon, 2013) and between those constructs to academic performance (Komarraju & Nadler, 2013; Zimmerman, 1990). This study suggests students who use motivational regulation strategies at medium and high levels may be more effective in regulating other aspects of learning (metacognition) and developing their personal beliefs about their abilities to succeed, which will then positively impact their academic achievement. This supports the theory of a larger self-regulatory system that encompasses different aspects of motivation and regulation related to academic achievement (Wolters, 2003; Zimmerman, 2011). Understanding more in-depth the link between motivational regulation strategies and other self-regulated learning variables is an area for future study.

In addition, unlike previous studies (Grunschel et al., 2016), this study did *not* show that academic procrastination was a mediator. Added to this was the finding that, in this sample, academic procrastination and academic achievement were positively correlated. This is in contrast to research showing that academic procrastination and academic performance is generally negatively correlated (average effect size r = -.13; Kim & Seo, 2015). Students in this sample may be using academic procrastination as a strategy for performance. There is some evidence suggesting that not all types of procrastination are negative; there is a form of active procrastination, defined as the type to postpone tasks to deliberately focus on priorities, that was positively correlated with GPA (Chu & Choi, 2005). Further research, however, needs to be conducted to explore this in-depth.

Overall, findings from this study suggest a complex process by which motivational regulation strategies may impact performance. Individuals who are effective at using strategies to regulate their motivation are also more likely to use other strategies to regulate cognition and self-motivating beliefs, which then contribute to improved performance. Results, then, suggest taking a focused, direct approach to developing individuals' motivation. This means not only understanding their motivation factors, but also their processes and strategies to maintain motivation. People are integral to organizations, and motivation is a crucial element in developing the human capital (Muscalu & Muntean, 2013).

Limitations and Future Directions

This study is limited in several ways. First, this was a cross-sectional study where variables were collected at the same time. This limits our ability to evaluate causal relations among variables and results are only suggestive. Future studies should take into account the temporal aspects of each variable. Second, participants for this study were diverse in the areas of academic study. It is possible that there are individual differences in the use of motivational regulation strategies among subgroups (e.g., class, majors). A multi-group analysis would be able to test this hypothesis. Third, the questionnaire used in the study was all self-report, so there may be an aspect of self-report bias or social desirability. Finally, to continue developing this measure, more evidence needs to be collected, particularly to explore if the profiles found in this study can be replicated in other samples. Despite the limitations, this study provides a better understanding of the individual differences in use of motivational regulation strategies. This will help researchers, parents, educations, and managers identify ways to intervene and support individuals' motivational challenges.

Practical Implications and Conclusion

In conclusion, findings from this study supported and expanded the existing literature. First, this study provided validity evidence for a revised measure of motivational regulation strategies that included strategies from other measures (Wang, 2013; Schwinger et al., 2009) not yet tested with an English sample. Second, findings provided additional empirical support for three distinct profiles of motivational regulation strategies usage in line with and extending previous works (Reindl et al., 2020; Schwinger et al., 2012). Lastly, the findings suggest complexity in students' learning behavior. Motivational regulation strategies by themselves do not directly contribute to academic outcomes, but only when it serves to increase students' use of effective cognitive strategies and beliefs in their performance.

The concepts and theoretical framework used in this study not only has a deep history in education, but also has been widely applied in the field of management, broadly defined as work motivation theory. Understanding employees' motivation has always been an important factor in understanding the organization. Previous frameworks, however, have not directly addressed the dynamic nature of motivation, how it can fluctuate over time or how it can be directly regulated by individuals. Results are directly applicable to areas of management and how we can use individual motivational regulation mechanism for better outcomes. For example, managing employees may include understanding their motivational profile (factors that motivate, including salary and competency) as well as their strategies (how they deal with changing motivation levels) that may directly impact their behaviors, which will impact overall performance. Furthermore, though much research has focused on individual-level mechanism, the theory can also be extended to apply to the organization as whole. Organizations are also dynamic places where goals, interests, and motivations shift. How organizations adjust and adapt to these motivational challenges is an area for future research. Motivation is essential to performance: understanding the nuances of what motivates individuals and organizations is key to creating environments where people thrive and organizations innovate.

REFERENCES

American Educational Research Association, American Psychological Association, National Council on Measurement in Education, Joint Committee on Standards for Educational and Psychological Testing (U.S.). (2014). *Standards for educational and psychological testing*. Washington, DC: AERA.

Barry, C.L., & Finney, S.J. (2009). Can we feel confident in how we measure college confidence? A psychometric investigation of the College Self-Efficacy Inventory. *Measurement and Evaluation in Counseling and Development*, *42*(3), 197-222.

Bergman, L.R., & Andersson, H. (2010). The person and the variable in developmental psychology. *Journal of Psychology*, *218*(3), 155-165.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European Psychologist*, *1*(2), 100-112.

Bollen, K.A. (1980). Issues in the comparative measurement of political democracy. *American Sociological Review*, *45*(3), 370–390. doi:10.2307/2095172

Brown, T.A. (2006). Other types of CFA models: Higher-order factor analysis, scale reliability evaluation, and formative indicators. In *Confirmatory factor analysis for applied research* (pp. 287-331). New York: Guilford Press.

Chow, B. (2011). *Regulation of motivation in undergraduate business students learning with the case method: Examining an underemphasized aspect of self-regulated learning* (Doctoral Dissertation). Retrieved from http://summit.sfu.ca/

DeNisi, A.S., & Pritchard, R.D. (2006). Performance appraisal, performance management and improving individual performance: A motivational framework. *Management and Organization Review*, *2*(2), 253-277.

Eccles, J.S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109-132.

Elliot, A.J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist*, *34*(3), 169-189.

George, D., & Mallery, M. (2010). *SPSS for Windows Step by Step: A Simple Guide and Reference* (10th ed., pp. 112-119). Boston, MA: Pearson.

Grunschel, C., Schwinger, M., Steinmayr, R., & Fries, S. (2016). Effects of using motivational regulation strategies on students' academic procrastination, academic performance, and well-being. *Learning and Individual Differences*, *49*, 162–170.

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

Komarraju, M., & Nadler, D. (2013). Self-efficacy and academic achievement: Why do implicit beliefs, goals, and effort regulation matter? *Learning and Individual Differences*, *25*, 67-72.

Kim, Y., Brady, A.C., & Wolters, C.A. (2018). Development and validation of the brief regulation of motivation scale. *Learning and Individual Differences*, *67*, 259-265.

Kim, K.R., & Seo, E.H. (2015). The relationship between procrastination and academic performance: A meta-analysis. *Personality and Individual Differences*, *82*, 26-33.

Krapp, A. (2002). Structural and dynamic aspects of interest development: Theoretical considerations from an ontogenetic perspective. *Learning and Instruction*, *12*, 383–409.

Kuhl, J., & Kraska, K. (1989). Self-regulation and metamotivation: Computational mechanisms, development, and assessment. In R. Kanfer, P.L. Ackerman, & R. Cudeck (Eds.), *Abilities, motivation, and methodology: The Minnesota symposium on individual differences* (pp. 343-374). Hillsdale, NJ: Erlbaum.

Locke, E.A., & Latham, G.P. (2002). Building a practically useful theory of goal setting and task motivation. *American Psychologist*, *57*(9), 705-717.

Locke, E.A., & Latham, G.P. (2006). New directions in goal-setting theory. *Current Directions in Psychological Science*, *15*(5), 265-268

Marsh, H.W., Lüdtke, O., Trautwein, U., & Morin, A.J.S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*, 191–225. doi:10.1080/10705510902751010

Maslow, A.H. (1943). A theory of human motivation. *Psychological Review*, *50*(4), 370–396.

McCann, E.J., & Garcia, T. (1999). Maintaining motivation and regulating emotion: Measuring individual differences in academic volitional strategies. *Learning and Individual Differences*, *11*(3), 259-279.

Miele, D.B., & Scholer, A.A. (2016). Self-regulation of motivation. In (Eds.), *Handbook of motivation at school* (2nd edition). New York: Routledge.

Muscalu, E., & Muntean, S. (2013). Motivation - a stimulating factor for increasing human resource management performance. *Review of International Comparative Management*, *14*(2), 303-309.

Norem, J.K., & Illingworth, K.S. (1993). Strategy-dependent effects of reflecting on self and tasks: Some implications of optimism and defensive pessimism. *Journal of Personality and Social Psychology*, *65*(4), 822-835.

Pintrich, P.R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology*, *95*(4), 667-686.

Pintrich, P.R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, *16*(4), 385-407.

Pintrich, P.R., Smith, D.A.F., Garcia, T., & McKeachie, W.J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Ann Arbor: University of Michigan, National Center for Research to Improve Postsecondary Teaching and Learning.

Raykov, T. (2001). Estimation of congeneric scale reliability using covariance structure analysis with nonlinear constraints. *British Journal of Mathematical and Statistical Psychology*, *54*(2), 315-323.

Reindl, M., Tulis, M., & Dresel, M. (2020). Profiles of emotional and motivational self-regulation following errors: Associations with learning. *Learning and Individual Differences*, *70*, 101806.

Sansone, C., & Thoman, D.B. (2005). Interest as the missing motivator in self-regulation. *European Psychologist*, *10*(3), 175–186.

Schwinger, M., Steinmayr, R., & Spinath, B. (2009). How do motivational regulation strategies affect achievement: Mediated by effort management and moderated by intelligence. *Learning and Individual Differences*, *19*, 621-627.

Schwinger, M., Steinmayr, R., & Spinath, B. (2012). Not all roads lead to Rome—comparing different types of motivational regulation profiles. *Learning and Individual Differences*, *22*, 269-279.

Schwinger, M., & Stiensmeier-Pelster, J. (2012). Effects of motivational regulation on effort and achievement: A mediation model. *International Journal of Educational Research*, *56*, 35-47.

Smit, K., Brabander, C.J., Boekaerts, M., & Martens, R.L. (2017). The self-regulation of motivation: Motivational strategies as mediator between motivational beliefs and engagement for learning. *International Journal of Educational Research*, *82*, 124–134.

Steers, R.M., Mowday, R.T., & Shapiro, D.L. (2004). The future of work motivation theory. *Academy of Management Review*, *29*(3), 379-387.

Trang, K.T., & Hansen, D.M. (2018). *A measure of motivation regulation strategies for academic tasks*. Unpublished manuscript.

Van den Broeck, A., Carpini, J., & Diefendorff, J. (2019). How much effort will I put into my work? It depends on your type of motivation. In R. Ryan (Ed), *Oxford Handbook of Human Motivation*, (2nd edition, pp. 354-372). John Wiley & Sons. DOI: 10.1093/oxfordhb/9780190666453.013.27

Wang, C. (2013). *Achievement goals, motivational self-regulation, and academic adjustment among elite Chinese high school students* (Doctoral dissertation, Ball State University). Retrieved from http:// http://core.kmi.open.ac.uk/

Wang, J., & Wang, X. (2019). *Structural equation modeling: Applications using Mplus* (pp. 339-443). John Wiley & Sons.

Wigfield, A., & Eccles, J.S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*, 68–81.
Wolters, C.A (1999). The relation between high school students' motivational regulation and their use of learning strategies, effort, and classroom performance. *Learning and Individual Differences*, *3*(3), 281-299.
Wolters, C.A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist*, *38*(4), 189-205.
Wolters, C.A. (2011). Regulation of motivation: Contextual and social aspects. *Teachers College Record*, *113*(2), 265-283.
Wolters, C.A., & Benzon, M.B. (2013). Assessing and predicting college students' use of strategies for the self-regulation of motivation. *The Journal of Experimental Education*, *81*(2), 199-221.
Wolters, C.A., Benzon, M.B., & Arroyo-Giner, C. (2011). Assessing strategies for the self-regulation of motivation. In B.J. Zimmerman, & D.H. Schunk (Eds.), *Handbook of self-regulation of learning and performanc*e (pp. 298-312). New York: Taylor & Francis.
Yockey, R.D. (2016). Validation of the short form of the Academic Procrastination Scale. *Psychological Reports*, *118*(1), 171-179.
Zimmerman, B.J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3-17.
Zimmerman, B.J. (2011). Motivational sources and outcomes of self-regulated learning and performance. In B.J. Zimmerman, & D.H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 49-64). New York: Taylor & Francis.
Zimmerman, B.J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology*, *82*(1), 51-59.